ABSTRACT

Title of Dissertation: FOOD PRODUCT RECALLS: TRENDS AND DEMAND IMPACTS

Elina Tselepidakis, Doctor of Philosophy, 2016

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Food product recalls, the removal of risky food products from the marketplace, can impose significant burdens for consumers, producers, and regulators. The purpose of this dissertation is to offer an in-depth investigation of the trends and demand impacts of food product recalls. The first objective is to analyze trends and patterns of food product recall events from 2004 to 2013. The analysis considers multiple factors, including the types of foods being recalled, the reasons for initiating the recalls, the severity of the risks posed by the recalled products, and the geographic distribution. The second objective is develop a general Bayesian model to illustrate how consumers form perceptions of risk based on personal experiences and external signals, such as recall events. The model illustrates frequently observed behavior following the release of negative information: an immediate change in behavior, followed by a gradual return to previous, routine behavior. The third objective is to estimate the impact of leafy green recall events on the demand for packaged leafy green products by analyzing disaggregated household purchasing data. The results of this analysis suggests that iceberg and romaine recall events negatively impacted demand for the implicated leafy green in the weeks immediately following the recall. The fourth objective is to estimate the impact of STEC-contaminated ground beef

recall events on the demand for ground beef products, differentiating between recalls prompted by consumer illness investigations and those prompted by laboratory testing. The results suggest that the impacts of recalls prompted by consumer illnesses outbreaks were often greater in magnitude and lasted longer than the impacts of recalls prompted by pathogen testing.

FOOD PRODUCT RECALLS: TRENDS AND DEMAND IMPACTS

by

Elina Tselepidakis

Dissertation submitted to the Faculty of the Graduate School of the
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For my

father,

mother,

and

husband.

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Prior to making my decision for graduate school, I sought the counsel of an undergraduate mentor, Lee Benham. He advised me to think of graduate school as boarding a whaling ship for a five year voyage (or as it turned out in my case, seven). Once I left port, my world would be this boat, so I had to be sure to assess the crew and particularly the captains carefully. Indeed, the extraordinary crew and captains at University of Maryland were instrumental to my success. It was only with the support of my family, peers, and mentors that was I able to steer my way through rough waters and survive what seemed to be a never-ending voyage at sea.

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And as far the whale - well, I suppose this is it...

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List of Abbreviations

BSE	Bovine Spongiform Encephalopathy
CDC	Centers for Disease Control and Prevention
FALCPA	Food Allergen Labeling and Consumer Protection Act
FDA	Food and Drug Administration
FE	Fixed Effects
FoodNet	Foodborne Diseases Active Surveillance Network
FSIS	Food Safety and Inspection Service
FSMA	Food Safety Modernization Act
GMA	Grocery Manufacturers Association
HVP	Hydrolyzed Vegetable Protein
IRI	Information Resources, Inc.
LPM	Linear Probability Model
OLS	Ordinary Least Squares
PCA	Peanut Corporation of America
RE	Random Effects
RFR	Reportable Food Registry
STEC	Shiga toxin-producing Escherichia coli
UPC	Universal Product Code
USDA	United State Department of Agriculture

Introduction

Unsafe contaminated foods are responsible for millions of illnesses and lead to significant losses in life and productivity. The Centers for Disease Control and Prevention [CDC] estimate that foodborne disease is the cause of approximately 48 million illnesses, 128,000 hospitalizations, and 3,000 deaths annually within the United States (Scallan et al. 2011a and 2011b). Put another way, each year, one in six Americans becomes ill from consuming contaminated food products. Only 20 percent of these illnesses can be attributed to a specific pathogen, and in fiscal terms, these 9.4 million illnesses impose an estimated annual cost of 15.5 billion dollars covering medical expenditures, lost productivity, and quality of life losses (Hoffman et al. 2015). Fiscal estimates accounting for all foodborne illnesses are upwards of 55.5 to 77.7 billion dollars (Scharff 2012, Scharff 2015).

To evaluate trends in foodborne disease, the Foodborne Diseases Active Surveillance Network of the CDC, or FoodNet, has been tracking infections commonly transmitted through food since 1996 by monitoring 15 percent of the national population through FoodNet personnel located at state health departments. The most recent surveillance data from 2014 as compared to surveillance data from 2006 to 2008 show that the incidence of *Campylobacter*[1] has increased by 11 percent and the incidence of *Vibrio*[2] has increased by an alarming 54 percent. When compared to surveillance data from 2011 to 2013, the incidence of non-O157 Shiga toxin-producing *Escherichia coli*

[1] *Campylobacter* is a spiral-shaped bacteria that can cause disease in humans and animals. Most cases of campylobacteriosis are associated with eating raw or undercooked poultry meat or from cross-contamination of other foods by these items.

[2] *Vibrio* is a rod-shaped bacteria which can cause foodborne illness and is usually associated with eating undercooked seafood, usually raw oysters.

[STEC] has increased by 22 percent.[3] In contrast, incidences of *Salmonella* and *Listeria* have largely remained unchanged, though have improved in the long run when compared to figures from the first few years of monitoring, 1996 to 1998. Taken all together, a recent analysis of FoodNet data by Powell (2016) determined that between 1996 and 2013 there has been no overall reduction in illnesses due to foodborne bacterial pathogens.

The industry-wide provision of unsafe foods, resulting in these non-decreasing trends in foodborne illnesses, illustrates the inherent risks in the growing, harvesting, processing, packing, and distribution of food products. The central obstacle is one of imperfect information. Consumers do not know with certainty what risks are present in the foods they purchase and consume. Thus, consumers cannot differentiate products based on safety as they can with many other product attributes, such as taste and appearance. Despite preferences to avoid risky goods, consumers may unknowingly purchase unsafe products because of this inability to differentiate products based on safety attributes. Producers, in contrast, have more knowledge of product safety than consumers because producers know the safety measures employed to reduce the risk of contamination during production. However, producers also don’t have complete perfect information in that they also cannot state with certainty whether a product is contaminated or not, unless each product is reliably tested for contamination. This asymmetry and lack of information ultimately leads to market failure because if consumers cannot differentiate products based on health risks, producers lose incentive to employ safe production practices. Therefore, the challenge for food safety regulators is to

[3] Comparisons of non-O157 STEC incidence to earlier time periods are not available.

implement policies so that markets characterized by imperfect information can function efficiently. These policies include statutory regulation and government oversight.

Both federal and state governments engage in preventive actions to protect consumers from unsafe foods, including inspection, sampling, recalls, and research. Food product recalls, the removal of risky food products from the marketplace, can have particularly significant impacts for both consumers and producers, and are the central focus of this dissertation. The following five chapters investigate both general trends and consumer responses to food product recalls. The first chapter analyzes trends and patterns in food product recall events over the course of a decade, 2004 to 2013. The second chapter reviews the extensive literature on the impact of food safety information on consumer demand. The third chapter develops a general model to illustrate how consumers form perceptions of risk based on personal experiences and external signals, and how perception of risk may in turn impact demand. The fourth chapter estimates the impact of leafy green recall events on the demand for packaged leafy green products from 2008 to 2012. Lastly, the fifth chapter estimates the impact of STEC-contaminated ground beef recall events on the demand for ground beef products from 2008 to 2012, differentiating between recalls prompted by consumer illness investigations and those prompted by laboratory testing.

I. Trends in Food Product Recalls: 2004-2013

In an effort to protect public health and prevent foodborne illness, the federal government takes measures to ensure that the nation's food supply is safe, wholesome, and accurately labeled. These measures include overseeing the removal of risky food products from the market. While removal of risky and potentially contaminated goods from the market benefits the public at large, the direct and indirect costs to manufacturers and regulators can be substantial. According to a recent survey conducted by the Grocery Manufacturers Association [GMA], 29 percent of companies that had faced a recall within the past five years estimated that the direct cost of the recall was between 10 and 29 million dollars (GMA 2011). These direct costs include notification (to regulatory bodies, the downstream supply chain, and consumers), customer reimbursement, product retrieval, storage and destruction, business interruption, and loss of sales of the recalled product. The total cost can be more extensive when accounting for indirect costs, including the cost of any subsequent litigation and the impact on the manufacturer's market value and brand reputation. Additionally, these costs can often spillover and impact other manufacturers within the same industry, particularly for products that are marketed collectively. When a product is marketed collectively and has little to no brand differentiation, consumers may react by avoiding the commodity as a whole and the reputation of the entire industry may be tarnished.

Food product recalls also pose a great concern for consumers. Many consumers deem recalls to be negative signals that convey information about the relative safety of a food product, and concerns of unsafe food products and foodborne disease have the strong potential to influence consumer purchases and demand. Additionally, the burden of information falls on the consumer to remain informed of current product recalls and to monitor home inventories. A national survey of consumer awareness of food product recalls revealed that 84 percent of 1,100 respondents had heard of at least one of three recent recall events, but less than half (45 percent) knew that there is always at least one food product recall in effect at any given time. The majority of respondents (59 percent) also reported having searched for a recalled product at some point in their own home (Hallman, Cuite, and Hooker 2009).

Over the past decade, the total number of food product recall events has increased considerably. Given the substantial direct and indirect costs of recalls on manufacturers, consumers, and regulators, there is a fundamental need to understand the origin and reasons behind the general increase in the total number of food product recalls. The primary objective of this chapter is to analyze trends, patterns, causes, and outliers in food product recalls over the course of a decade, 2004 to 2013. Specifically, trends are identified by the types of food products being recalled, the reasons for initiating recalls, the health risk severity posed by the recalled products, and the geographic distribution of recalled products. Identification of trends and patterns may provide targets for both manufacturer food safety practices and regulatory oversight, which may ultimately aid in reducing the total number of recalls. This could potentially lead to a reduction in excessive recall costs, improve the overall quality and safety of the food supply, and result in fewer foodborne illness outbreaks.

The period chosen for analysis, 2004 to 2013, is a critical period with regards to food safety in the United States. During this time, there were several major highly-publicized foodborne illness outbreaks linked to contaminated products, notably spinach (2006), peanut butter (2009), eggs (2010), and cantaloupe (2011). Additionally, two major pieces of food safety legislation were signed into law: the Food Allergen Labeling and Consumer Protection Act [FALCPA] of 2004, which requires all food labels to list major allergens, and the Food Safety Modernization Act [FSMA], which gives FDA the authority to impose mandatory recalls and, if necessary, shut down operations at food production facilities.

Background

Within the United States, the two primary federal authorities responsible for food safety are the Department of Agriculture's [USDA] Food Safety and Inspection Service [FSIS] and the Department of Health and Human Services' Food and Drug Administration [FDA]. The FSIS inspects and regulates meat, poultry, and processed egg products, and, as a result of the 2008 and 2014 Farm Bills, also inspects fish of the order Siluriformes (e.g., catfish)[4] (USDA FSIS 2015). The FDA inspects and regulates all other food products, including sandwiches (made in central facilities for off-site consumption), certain products that contain a small amount of meat and poultry (by volume), and game and exotic meats.[5] This division of responsibilities dates back to 1906 when Congress passed two separate acts that charged one branch of the USDA with inspecting meat (the Meat Inspection Act) and the predecessor of the FDA with ensuring the safety of all other foods (the Pure Food and Drugs Act). The former addressed the unsafe and unsanitary conditions in meat packing plants and the latter addressed the widespread marketing of intentionally adulterated foods (Johnson 2014). Over the past couple decades, the

[4] FSIS inspection of catfish became effective March 1, 2016.
[5] The FDA also ensures the safety of drugs, dietary supplements, medical devices, animal feed, tobacco, and cosmetics, but for the purposes of this study, only food products are considered.

Government Accountability Office has published several reports highlighting the inefficiencies of this divided system and has recommended broad restructuring of the nation's food safety oversight (see, for example, Dyckman 2004).

Nonetheless, both FSIS and FDA currently coordinate and oversee the recalls of products that may cause increased health risks. Examples of possible health risks include pathogen contamination, foreign object contamination, undeclared allergens, and undeclared sulfites. Health risks are usually discovered one of several ways: the manufacturer or distributer, USDA or FDA, or a state agency discovers the presence of a health risk through testing or inspection; a consumer inquires or files a complaint against a specific product; or a consumer illness prompts an investigation and the source of illness is traced back to a specific product and manufacturer. As soon as the threat is discovered and the manufacturer decides (or is mandated) to recall the contaminated product, the FSIS or FDA determines the severity of the threat posed by the marketed product and assigns the recall one of three classifications: Class I, II, or III. Class I represents a health hazard situation in which there is reasonable probability that consuming the product will cause health problems or death; Class II represents a potential health hazard situation in which there is a remote probability of adverse health consequences from the consumption of the product; and Class III represents a situation in which consuming the product will not cause adverse health consequences. The same classification system is used by both the FDA and FSIS.

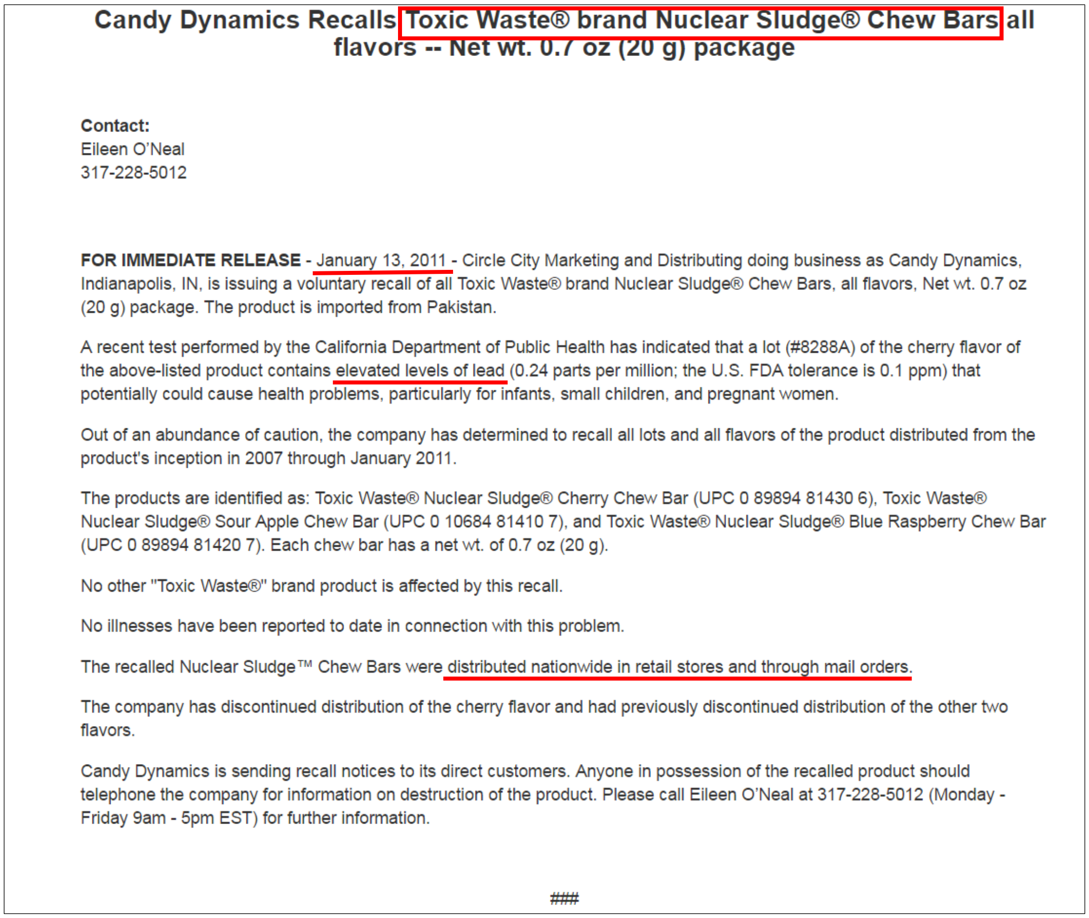
Lastly, FSIS, FDA, and/or the manufacturer usually issues a press release to vendors and media outlets in the areas where the recalled product was distributed. Vendors of the recalled product are instructed to remove the product from the market so that it is no longer available for purchase or consumption. Likewise, consumers are instructed to check any products they may have purchased before the recall announcement and determine whether products in their pantry or refrigerator match the description of the contaminated product. If the description is a match, consumers are strongly encouraged to discard the product or return the product for a refund. If a consumer has already consumed the product, the consumer is instructed to closely monitor his or her health and seek any necessary medical attention.

Data

The FSIS issues a press release for almost every recall event under their authority. Conversely, the FDA will seek media publicity when the situation warrants widespread public awareness, for example, the nationwide distribution of a Class I recalled product. While not all FDA recalls are publicized with press releases, all recalls monitored by the FDA are included in FDA Enforcement Reports once the recalls have been classified according to the level of hazard involved. Together, the FDA and FSIS press releases and the FDA Enforcement Reports, archived and available to the public online, provide a complete picture of food products recalled in the United States.[6] The press releases include the date of the FDA or FSIS recall announcement, a description of the product(s) recalled, the reason for the recall and the health risk involved, and the distribution of the contaminated product. In addition, the press releases sometimes include information on how the health risk was discovered and whether the contaminated product was available

[6] Though there is significant overlap, these data differ from Reportable Food Registry [RFR], which is an electronic portal for industry to report food products when there is reasonable probability that the product will cause serious adverse health consequences. The RFR is maintained by the FDA and applies to all FDA-regulated categories of food and feed.

for retail purchase or distributed to restaurants and institutional facilities (schools, prisons, nursing homes, etc.). FDA Enforcement Reports can be used to verify the information contained within the press release, and also include the severity classification and the quantity of the product recalled. Examples of an FDA press release and the corresponding entry in the FDA Enforcement Report are presented in figures 1 and 2, respectively.



Candy Dynamics Recalls Toxic Waste® brand Nuclear Sludge® Chew Bars all flavors -- Net wt. 0.7 oz (20 g) package

Contact:
Eileen O'Neal
317-228-5012

FOR IMMEDIATE RELEASE - January 13, 2011 - Circle City Marketing and Distributing doing business as Candy Dynamics, Indianapolis, IN, is issuing a voluntary recall of all Toxic Waste® brand Nuclear Sludge® Chew Bars, all flavors, Net wt. 0.7 oz (20 g) package. The product is imported from Pakistan.

A recent test performed by the California Department of Public Health has indicated that a lot (#8288A) of the cherry flavor of the above-listed product contains elevated levels of lead (0.24 parts per million; the U.S. FDA tolerance is 0.1 ppm) that potentially could cause health problems, particularly for infants, small children, and pregnant women.

Out of an abundance of caution, the company has determined to recall all lots and all flavors of the product distributed from the product's inception in 2007 through January 2011.

The products are identified as: Toxic Waste® Nuclear Sludge® Cherry Chew Bar (UPC 0 89894 81430 6), Toxic Waste® Nuclear Sludge® Sour Apple Chew Bar (UPC 0 10684 81410 7), and Toxic Waste® Nuclear Sludge® Blue Raspberry Chew Bar (UPC 0 89894 81420 7). Each chew bar has a net wt. of 0.7 oz (20 g).

No other "Toxic Waste®" brand product is affected by this recall.

No illnesses have been reported to date in connection with this problem.

The recalled Nuclear Sludge™ Chew Bars were distributed nationwide in retail stores and through mail orders.

The company has discontinued distribution of the cherry flavor and had previously discontinued distribution of the other two flavors.

Candy Dynamics is sending recall notices to its direct customers. Anyone in possession of the recalled product should telephone the company for information on destruction of the product. Please call Eileen O'Neal at 317-228-5012 (Monday - Friday 9am - 5pm EST) for further information.

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Figure 1. Example of an FDA Press Release, January 13, 2011. Emphasis added.

RECALLS AND FIELD CORRECTIONS: FOODS - CLASS II

PRODUCT
1) Toxic Waste brand Nuclear Sludge Cherry Chew Bar, Net wt. 0.7 oz (20 g) package, UPC 89894 81430; and 0.3 oz (8 g) package, UPC 8989481901. Imported from Pakistan. Product is an ultra sour taffy-like candy bar. Described as "hazardously" sour candy. Recall # F-0731-2011;

2) Toxic Waste brand Nuclear Sludge Sour Apple Chew Bar, Net wt. 0.7 oz (20 g) package, UPC 0 10684 81410 7; and Net wt. 0.3 oz (8 g) package, 8989481701. Imported from Pakistan. Product is an ultra sour taffy-like candy bar. Described as "hazardously" sour candy. Recall # F-0732-2011;

3) Toxic Waste brand Nuclear Sludge Blue Raspberry PLE Chew Bar, Net wt. 0.7 oz (20 g) package, UPC 89894 81420; and Net wt. 0.3 oz (8 g) package, UPC 8989481801. Imported from Pakistan. Product is an ultra sour taffy-like candy bar. Described as "hazardously" sour candy. Recall # F-0733-2011

CODE
Lot #8288A; All lots and all flavors of the product distributed from the product's inception in 2007 through January 2011.

RECALLING FIRM/MANUFACTURER
Recalling Firm: Circle City Marketing & Distributing, Carmel, IN, by press release on January 13, 2011 and January 27, 2011 and by letters beginning January 14, 2011.
Manufacturer: Asian Food Industries Ltd., Lahore, Pakistan. Firm initiated recall is ongoing.

REASON
A recent test performed by the California Department of Public Health has indicated that a lot (#8288A) of the Toxic Waste brand Nuclear Sludge Cherry Chew Bar contains elevated levels of lead (0.24 parts per million; the U.S. FDA tolerance is 0.1 ppm) that potentially could cause health problems, particularly for infants, small children, and pregnant women.

VOLUME OF PRODUCT IN COMMERCE
Undetermined

DISTRIBUTION
Nationwide, Canada, Korea, Italy, UK, Jordan, Denmark and Belgium

Figure 2. Example of an FDA Enforcement Report Entry. Emphasis added.

Between 2004 and 2013, the FDA and FSIS oversaw 4,900 food product recall events, and FSIS recalls of meat, poultry, and processed egg products accounted for 13 percent of all food product recall events (table 1). Generally, the incidence of both FDA and FSIS food recall events increased throughout the decade. Several possible factors may explain this trend, but conclusively stating a cause is difficult. One unlikely possibility is that food has generally been becoming less safe. While Hennessy, Roosen, and Jensen (2003) outlined systemic failures in the provision of safe food, it seems unlikely that any of the inherent deficiencies they identified would lead to an increase in the number of recalls within the past decade. Moreover, if this were the case and the food supply was in fact becoming less safe, we would also witness an increase in the number of reported foodborne illness outbreaks. However, Powell (2016) determined that from 1996 to 2013, there was neither a reduction nor an increase in illnesses due to bacterial pathogens commonly transmitted by food in the United States. Another possibility is that during this time, technology of pathogen and risk detection improved, thereby increasing the number of detected health risks in food products. Indeed, in recent years, there have been great improvements in rapid detection methods, which generally are more time-efficient, sensitive, specific, and labor-saving when compared to older, conventional methods (see Law et al. 2014 for a detailed review of rapid detection technologies). Alternatively, inspection efforts of federal and state agencies may have increased during this time, independent of technology improvements. Notably, the decade witnessed a change in federal administration in 2009, which may have impacted FDA and FSIS enforcement activities. Nguyen et al. (2013) found that the number of regulatory letters (i.e., warning letters and notices of violation) from the FDA to pharmaceutical companies was highest during the Clinton administration, diminished during the Bush administration, and increased again during the Obama administration.

Table 1. Total Number of Food Recall Events by Agency and Year

	FDA	**FSIS**
2004	298	49
2005	243	53
2006	211	34
2007	260	58
2008	263	53
2009	888	69
2010	469	70
2011	509	103
2012	664	82
2013	449	75
Total:	4,254	646

Lastly, the passage of two major food policy laws likely had major impacts on the incidence of food product recalls. The first, the Food Allergen Labeling and Consumer Protection Act [FALCPA] of 2004, effective January 1, 2006, requires all food labels to list major allergens. Under FALCPA and the Federal Food, Drug, and Cosmetic Act, the FDA, through inspections, ensures that food manufacturers comply with practices to reduce or eliminate cross-contact with allergens that are not intentional ingredients and ensures that major food allergens are properly labeled. Thus, FALCPA likely led to an increase in the incidence of food product recalls due to undeclared allergens. The second major law, the Food Safety Modernization Act [FSMA] of 2011, is the most sweeping reform of food safety law in over 70 years. Under FSMA, the FDA, for the first time, has the authority to impose a mandatory recall and shut down operations at food production facilities.[7] While FDA has only exercised this authority twice,[8] this new enforcement authority has the potential to change producer incentives to voluntarily disclose and recall risky products before being mandated to do so, leading to an increase in the number of food product recall events.

Examining recall events by the types of foods being recalled, health risks involved, severity, and distribution, may provide greater insight into specific outliers, trends, patterns, and causes behind this general increase in the total number of recall events between 2004 and 2013. Identification of any patterns and trends may also provide targets to focus regulatory oversight efforts.

[7] In contrast, FSIS does not have the authority to mandate recalls.

[8] As of August 2016, FDA has only mandated recalls twice: the 2013 recall of *Salmonella*-tainted pet treats and the 2014 recall of dietary supplements linked to a non-viral hepatitis outbreak.

Recalls by Food Categories

Seven main food groups were defined to categorize food recall events: grains, vegetables, fruit, dairy, meat and seafood, nuts, and other. These categories were further disaggregated into 99 individual categories outlined in Appendix A. These finer categories distinguish between different primary ingredients and various methods of preparation and packaging; for example, there are five root vegetable categories: fresh, frozen, canned, prepared, and dried. These categories were based on food categorization systems common in the nutrition literature, but adjusted to better suit the needs of food safety analysis. For example, following Painter et al. (2013), vegetable categories distinguish between fungi, leafy, root, sprouts, and vine-stalk vegetables, and meat categories distinguish between beef, pork, poultry, game, fish, crustaceans, and mollusks.

Table 2 lists the frequency of food product recall events by food type from 2004 to 2013. The top five food products recalled were prepared foods and meals, nuts and nut products, baked goods, grain products, and candy. With the exception of some nut products, these are all highly processed foods. It may be possible to gain further insight into the general increase in the number of food recall events by plotting selected major food categories over time. In doing so, we may be able to identify if any particular foods groups are predominantly responsible for the general increase and clearly identify outlier events (see figure 3).[9]

[9] In addition to the seven major food categories, three additional categories were also plotted (prepared meals, baked goods, and candy) given the high frequency of recalls in these categories.

Table 2. Total Number of Food Product Recall Events by Food Type, 2004-2013

Food Description	Frequency
Prepared Foods/Meals (excl. Soup)	581
Nuts, Seeds, & Nut Products	532
Baked Goods (incl. Packaged)	439
Grains (excl. Baked Goods)	412
Candy	388
Gravies, Sauces, Condiments, and Dressings	245
Fish and Fish Products	229
Beverages	219
Dairy-Based Desserts	211
Fruit and Fruit Products (excl. Juice)	210
Bacon, Sausage, and Lunch Meats	185
Beef and Beef Products	172
Cheese and Cheese Products	154
Spices and Seasonings	138
Soups	114
Root Vegetable Products	92
Leafy Vegetable Products	76
Poultry and Poultry Products	76
Mixed and Other Vegetable Products	66
Mollusks and Mollusk Products	65
Milk, Cream, and Yogurt Products	64
Vine-Stalk Vegetable Products	62
Nutrition Bars	57
Sprouts	47
Fruit Juice Products	46
Sweeteners/Jams/Jellies/Preserves	46
Crustaceans and Crustacean Products	46
Bean, Lentil, Peas, and Legume Products	39
Fungi Products	38
Uncategorized Products	36
Fresh Herbs	31
Tofu and Meat Substitutes	26
Pork and Pork Products	26
Eggs and Egg Mixtures	24
Baby Formula/Food	21
Fats and Oils	21
Vegetable Juices	7
Game, Lamb, and Other Meat Products	6
Total:	5,211

Note: The focus of this table is on food products rather than preparation; thus the 99 categories of Appendix A are aggregated into 38 categories. Additionally, the total number of food recall events by food type exceeds the total number of food recall events in Table 1 because 282 recall events include products in at least two different categories.

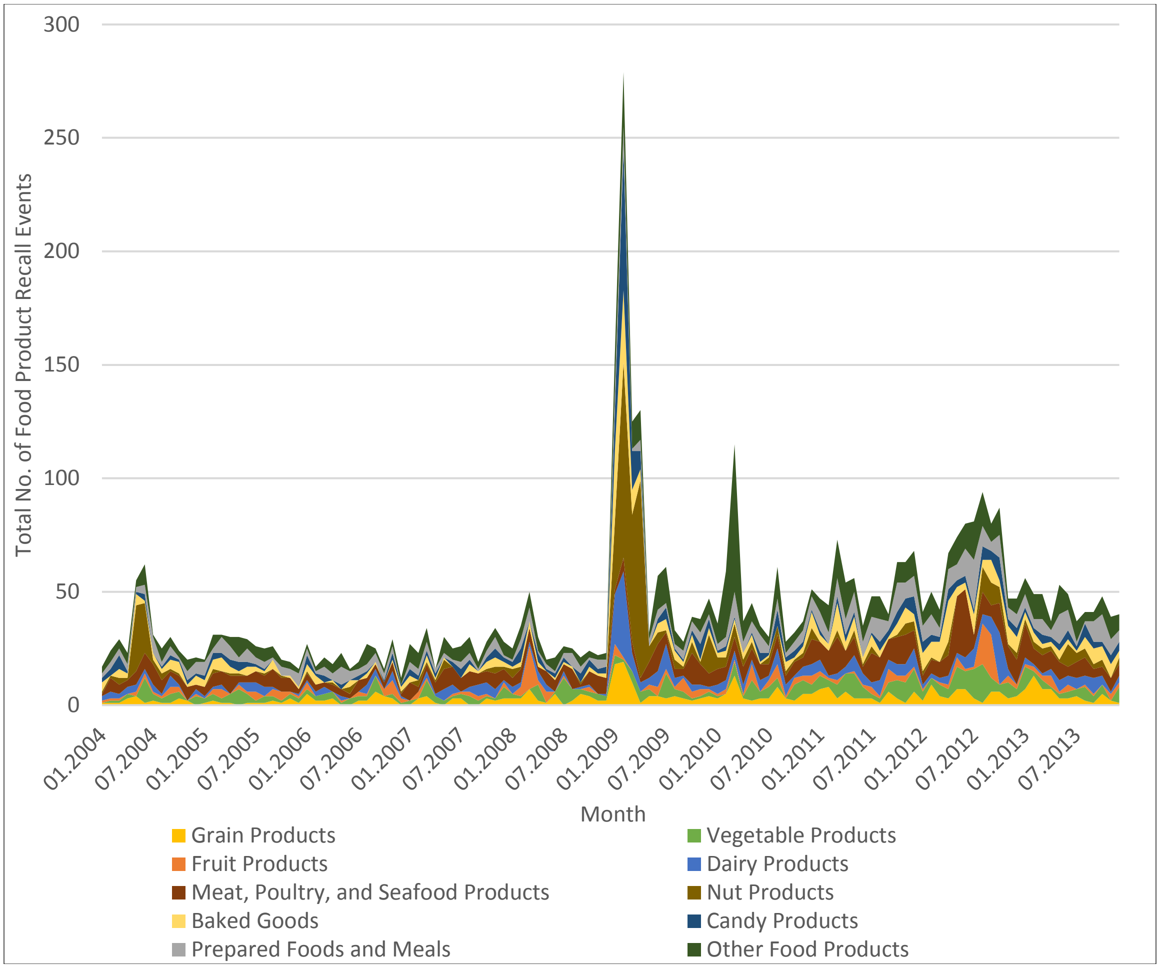

Figure 3. Food Product Recall Events by Food Type and Month, 2004-2013.

The most recognizable event is the January 2009 recall of peanut butter linked to a *Salmonella* outbreak responsible for 714 known illnesses and nine deaths. After peanut butter produced by Peanut Corporation of America [PCA] was implicated by epidemiologic and laboratory evidence, all identifiable food products that used PCA peanut butter and peanut paste as an ingredient were also recalled.[10] And because peanut butter and peanut paste are common ingredients in cookies, crackers, cereal, candy, ice cream, and other foods, over 400 separate recall events occurred as a consequence. As the

[10] The PCA outbreak is also notable for its subsequent criminal convictions. In September 2015, the former owner of PCA was sentenced to 28 years in federal prison for knowingly shipping *Salmonella*-tainted peanut butter, the harshest criminal sentence in a food safety case ever.

CDC (2009) stated, "this was an ingredient-driven outbreak, in which a contaminated ingredient affected many different products that [were] distributed through various channels and consumed in various settings."

Another uptick in the number of monthly food product recall events is the March/April 2009 recall of pistachios contaminated with *Salmonella*. Setton Farms of Terra Bella, the second largest producer of pistachios, recalled over one million pounds of roasted pistachio products just months after the massive PCA peanut butter recall. However, unlike the peanut butter product recall, the pistachio recall was not prompted by a consumer illness investigation, but instead prompted by FDA and commercial customer testing. Again, the pistachios were mostly sold to food wholesalers and manufacturers, who then packaged them for resale or incorporated them as ingredients in other products, such as ice cream and trail mix. In all, over 100 separate recall events were associated with the initial pistachio recall.

The final major outlier is the February 2010 recall of products containing hydrolyzed vegetable protein [HVP], a flavor enhancer. All products containing HVP (in powder and paste form) by a single manufacturer, Basic Food Flavors, were recalled because of possible *Salmonella* contamination. While this recall was again prompted by commercial customer testing rather than a consumer illness investigation, this is yet another example of an ingredient-driven recall. In total, over 80 recall events were associated with the initial recall of HVP; this included the recalls of spice blends, soups, sauces, gravies, dressing, etc.

While plotting the total number of food product recalls over time allows for clear identification of outliers, it is difficult to visually determine whether general time trends are present. However, we can compare averages from the first five years to the last five years and determine whether the differences are statistically significant. Table 3 presents the average number of annual recall events for selected food categories. Whereas the difference in means for 2004 to 2008 and 2009 to 2013 was *not* statistically significant for vegetable, fruit, nut, and candy products, the difference was statistically significant for animal products, baked goods, and prepared meals at the five percent level and for grain and other food products at the one percent level. Additionally, the difference in means for all food product recall events was statistically significant at the one percent level.

Table 3. Average Number of Annual Food Product Recall Events by Food Type, 2004-2013

	Average 2004-2013	**Average 2004-2008**	**Average 2009-2013**
Grain Products	41.2	24.4	58.0**
Vegetable Products	44.6	31.8	57.4
Fruit Products	25.6	20.2	31.0
Dairy Products	42.5	23.0	62.0*
Meat, Poultry, and Seafood Products	77.3	57.0	97.6*
Nut Products	53.2	19.2	87.2
Baked Goods	43.9	23.8	64.0*
Candy Products	38.8	22.6	55.0
Prepared Meals	58.0	38.6	77.4*
Other Food Products	89.9	54.2	125.6**
All Food Products	490.0	304.4	675.6**

Note: Asterisk (*) and double asterisk (**) indicate that the *t*-test of a difference in the means for 2004 to 2008 and 2009 to 2013 is significant at the five and one percent level, respectively.

Figures 4 and 5 plot the total number of annual fresh produce recall events and meat and seafood recall events, respectively. These foods are of particular interest as they represent the greatest health risk in terms of food safety. Produce and meat-poultry commodities accounted for the majority of foodborne illnesses, hospitalizations, and deaths between 1998 and 2008 (Painter et al. 2013). While the total number of fresh produce recall events appears to increase throughout the decade, the numbers drastically decreased in 2013. Therefore, only the difference in leafy green recall events for the first five years as compared to the last five years was statistically significant at the five percent level. Meat, poultry, and seafood recalls also did not significantly increase between the first and second half of the decade. However, the difference in means was statistically significant at the 10 percent level for processed meat, fish, and crustacean products.

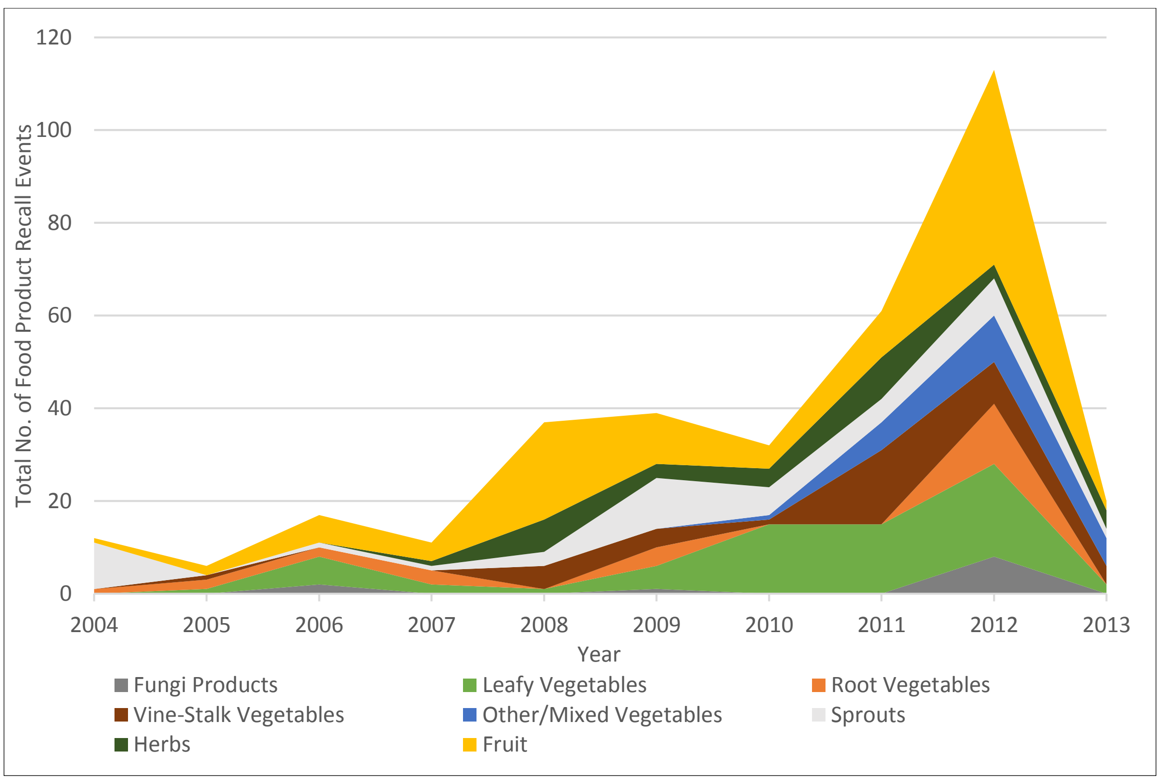

Figure 4. Fresh Produce Recall Events by Year, 2004-2013.

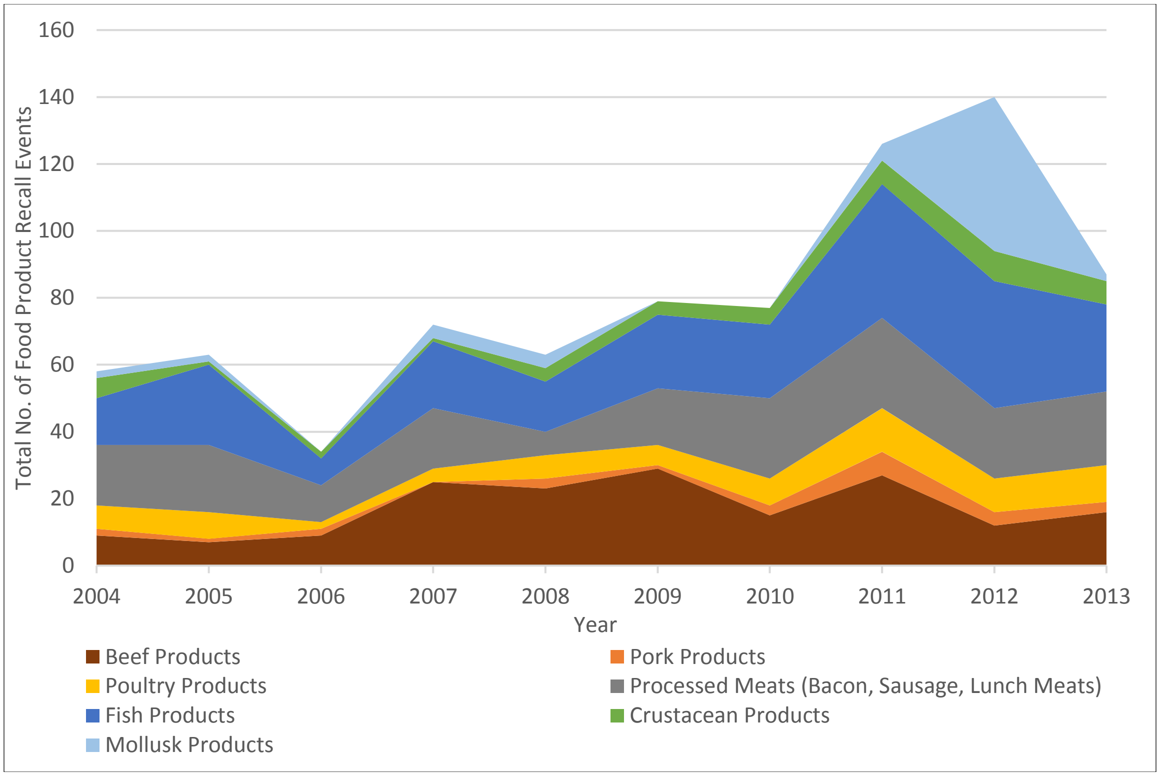

Figure 5. Meat, Poultry, and Seafood Recall Events by Year, 2004-2013.

Recalls by Health Risk

Recalls are initiated upon the discovery of a health risk. These health risks have been categorized into seven main groups: pathogen contamination, undeclared major allergens, undeclared substances, extraneous material, processing defects, mislabeling, and other. Pathogen contamination includes the discovery of Shiga toxin-producing *Escherichia coli* [STEC] (a sometimes life-threatening bacterium that produces Shiga toxin, which may cause severe abdominal cramps, diarrhea, and vomiting), *Salmonella* (a bacterium that may cause diarrhea, fever, and abdominal cramps), *Listeria monocytogenes* (a bacterium that may cause fever and muscle aches, particularly in older adults, pregnant women, and immunocompromised individuals), and other pathogens (such as, *Staphylococcus aureus*, *Clostridium botulinum*, *Lactobacillus*, etc.). Undeclared major allergens include the eight major allergens: wheat, eggs, peanuts, milk, tree nuts (e.g., almonds, pecans, and walnuts), soybeans, fish, and crustacean shellfish. Undeclared substances refer to food additives, such as sulfites, colors, aspartame, monosodium glutamate, etc. Extraneous material recalls occur when plastic fragments, metal shavings, latex pieces, or other foreign materials are inadvertently discovered in food products. Examples of processing defects include packaging defects, temperature abuse, improper pasteurization, and uneviscerated seafood among other possible processing errors. Mislabeling often refers to a packaging error, for example root beer bottled and mistakenly labeled as a cola beverage. Lastly, the other category includes risks and reasons that did not adequately fit into the first six categories, such as potential animal drug contamination, elevated levels of histamine, and inadequate pH levels. Table 4 lists the frequency of food product recall events by health risk from 2004 to 2013. Undeclared allergens were the leading cause of food product recall events, followed closely by concerns of possible *Salmonella* contamination.

Table 4. Total Number of Food Product Recall Events by Health Risk, 2004-2013

Health Risk (Reason for Recall)	Frequency
Undeclared Allergens	1,343
Salmonella	1, 308
Other Reasons	544
Listeria monocytogenes	502
STEC (Shiga toxin-producing *Escherichia coli)*	149
Undeclared Substances	480
Extraneous Material	256
Processing Defect	203
Mislabeling	151
Other Pathogens	60

Note: Ninety-six recall events were initiated for more than one reason. Additionally, health risk information was missing for one observation.

Table 5 lists the frequency of health risks for the top five recalled food products from table 2 between 2004 and 2013. For each of these foods with the exception of nut products, undeclared allergens was the number one reason products were recalled, accounting for 39 to 62 percent of product recalls. The next most frequent reason was concern for potential *Salmonella* contamination; though for prepared foods, potential *Listeria* contamination was the second most common reason.

Table 5. Health Risks for Selected Food Categories, 2004-2013

Health Risk	Frequency	Health Risk	Frequency
Prepared Foods (excl. Soup)	581	Grains (excl. Baked Goods)	412
Undeclared Allergens	242 (42%)	Undeclared Allergens	201 (49%)
Listeria monocytogenes	149 (26%)	*Salmonella*	86 (21%)
Salmonella	56 (10%)	Extraneous Material	50 (12%)
Extraneous Material	42 (7%)	Undeclared Substances	37 (9%)
Undeclared Substances	37 (6%)	Other Reasons	32 (8%)
Other Reasons	22 (4%)	Mislabeling	12 (3%)
Processing Defect	16 (3%)	Other Pathogens	3 (1%)
STEC	14 (2 %)	*Listeria monocytogenes*	1 (0%)
Mislabeling	14 (2%)	Processing Defect	1 (0%)
Other Pathogens	2 (0%)		
Nuts, Seeds, & Nut Products	532	Candy	388
Salmonella	423 (80%)	Undeclared Allergens	150 (39%)
Undeclared Allergens	52 (10%)	*Salmonella*	122 (31%)
Undeclared Substances	35 (7%)	Undeclared Substances	58 (15%)
Other Reasons	10 (2%)	Other Reasons	39 (10%)
Extraneous Material	9 (2%)	Extraneous Material	21 (5%)
Mislabeling	6 (1%)	Mislabeling	16 (4%)
Listeria monocytogenes	4 (1%)	STEC	1 (0%)
Processing Defect	2 (0%)	*Listeria monocytogenes*	1 (0 %)
STEC	1 (0%)	Processing Defect	1 (0%)
Baked Goods[a]	439		
Undeclared Allergens	274 (62%)		
Salmonella	80 (18%)		
Undeclared Substances	39 (9%)		
Extraneous Material	22 (5%)		
Other Reasons	16 (4%)		
Mislabeling	9 (2%)		
Other Pathogens	5 (1%)		
Listeria monocytogenes	3 (1%)		
STEC	1 (0%)		

[a] Health risk information is missing for one baked good observation.

By plotting the health risks over time, it may be possible to gain further insight into whether a particular health risk is predominantly responsible for the general increase in food product recalls and again identify outlier events (see figure 6). Once more, the ingredient-driven recalls of peanut butter, pistachios, and HVP due to possible *Salmonella* contamination are again immediately recognizable. Additionally, in contrast to *Salmonella* recalls that appear to be mostly attributable to outlier events, the number of undeclared allergen recalls appears to increase steadily throughout the decade. We can formally verify the existence of this trend and other trends by comparing averages from the first five years to the last five years and calculating statistically significant differences. These averages and calculations, presented in table 6, suggest that indeed the number of recalls attributable to undeclared allergens and mislabeling were significantly greater in the latter half of the decade than the former. And as suspected, the greatest difference in absolute terms was due to undeclared allergens.

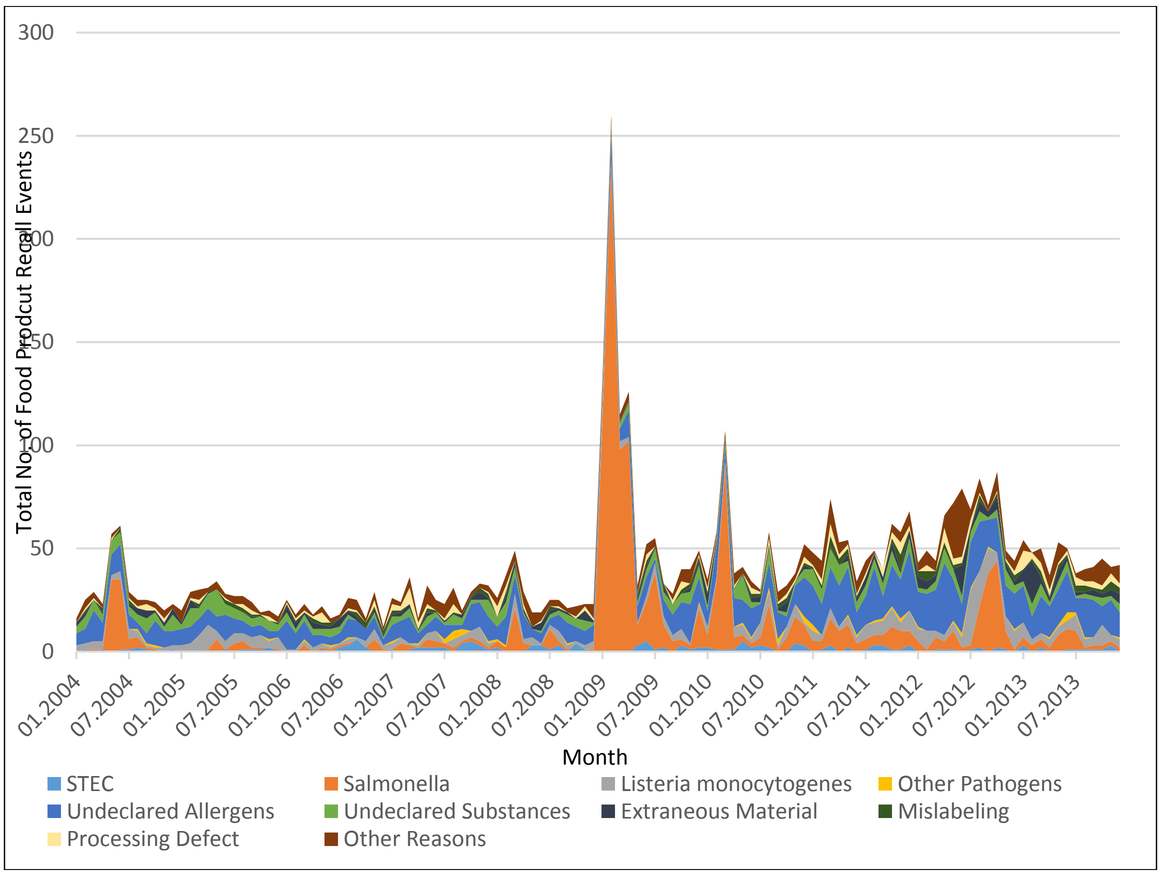

Figure 6. Food Product Recall Events by Health Risk and Month, 2004-2013.

Table 6. Average Number of Annual Food Product Recall Events by Health Risk, 2004-2013

	Average 2004-2013	Average 2004-2008	Average 2009-2013
STEC	14.9	13.6	16.2
Salmonella	130.8	36.2	225.4
Listeria monocytogenes	50.2	37.2	63.2
Other Pathogens	6.0	4.4	7.6
Undeclared Allergens	134.3	90.6	178.0*
Undeclared Substances	48.0	45.2	50.8
Extraneous Material	25.6	17.4	33.8
Processing Defect	20.3	10.4	19.8
Mislabeling	15.1	15	25.6*
Other Reasons	54.4	41.2	67.6

Note: Asterisk (*) and double asterisk (**) indicate that the *t*-test of a difference in the means for 2004 to 2008 and 2009 to 2013 is significant at the five and one percent level, respectively.

Figures 7 and 8 plot the annual health risks associated with fresh produce recall events and meat and seafood recall events, respectively. Bacterial pathogen contamination, specifically *Salmonella, Listeria monocytogenes*, and STEC, accounted for 92 percent of all produce recall events. In contrast, *Salmonella, Listeria*, and STEC contamination accounted for only 40 percent of meat, poultry, and seafood recall events. Additionally, the difference in meansbetween the first half of the decade and the second half was statisically siginacant at the five percent level for meat, poultry, and seafood recalls linked to *Salmonella* contamination, undeclared allergens, and undeclared substances.

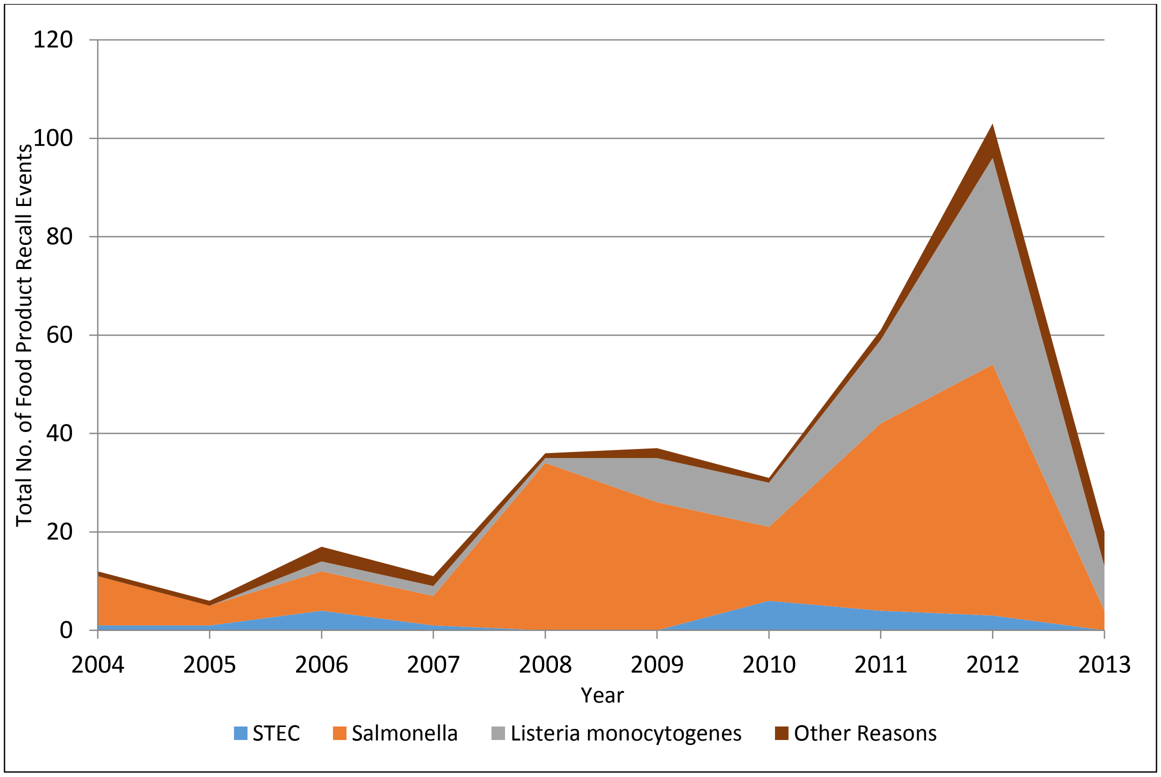

Figure 7. Fresh Produce Recall Events by Health Risk and Year, 2004-2013.

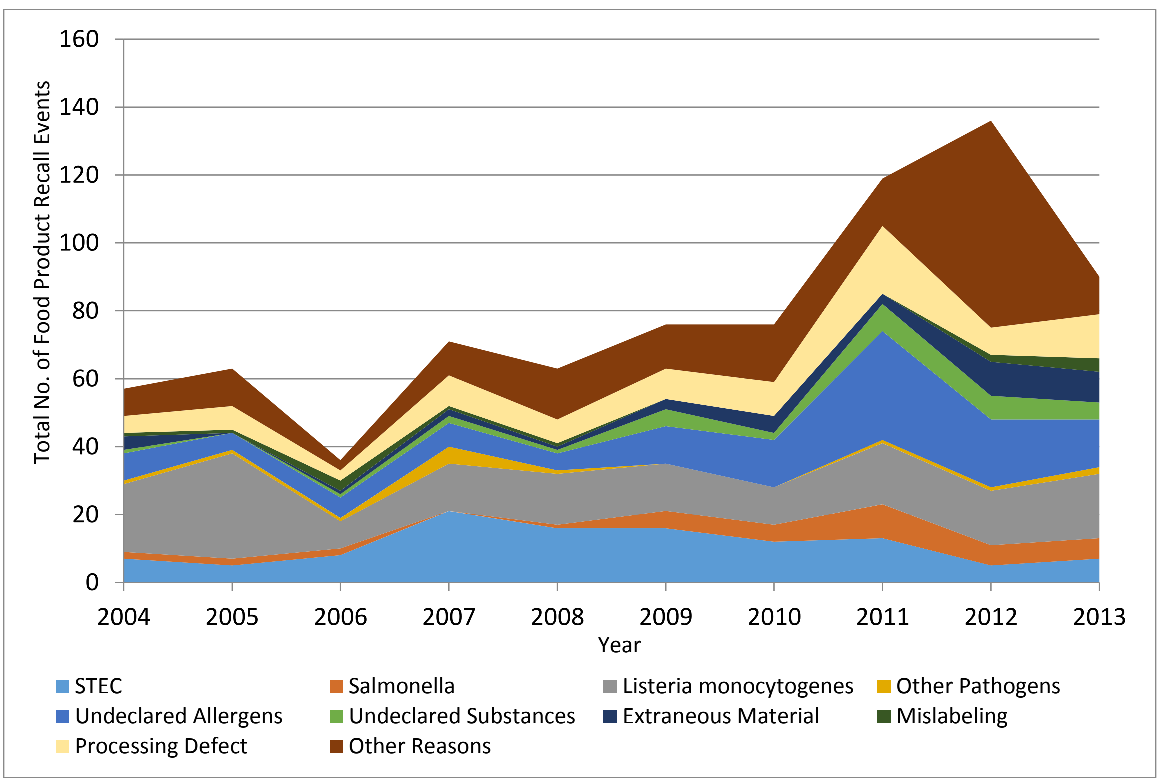

Figure 8. Meat, Poultry, and Seafood Recall Events by Health Risk and Year, 2004-2013.

Recalls by Health Risk Severity

Once a health risk is identified and a manufacturer decides to recall a product, the FDA or FSIS determines the severity of the health risk posed by the recalled product to the general public and categorizes the recall into one of three severity classifications. Class I represents a health hazard situation in which there is reasonable probability that consuming the product will cause health problems or potentially death; Class II represents a potential health hazard situation in which there is a remote probability of adverse health problems from the consumption of the product; and Class III represents a situation in which consuming the product will not cause adverse health consequences. Table 7 lists the total number of food product recall events by class and year from 2004 to 2013. For recalls with classification information, 61 percent of recalls were Class I recalls, 31 percent were Class II recalls, and 10 percent were Class III recalls. Note, however, that 493 recalls, 10 percent of all recall event observations, had missing classification information. All of these recalls (with the exception of one) were recalls overseen by the FDA. As previously noted, the source for FDA recall information was the FDA press releases and the FDA Enforcement Reports. While not all FDA recalls are publicized with press releases, all FDA recalls should be logged in FDA Enforcement Reports. The press releases contain a great deal of data, but the severity classification is noted only in the FDA Enforcement Reports. Of the 492 recalls overseen by the FDA with missing classification information, 97 percent (477 recalls) are recalls identified in press releases, but could not be matched to an entry in the FDA Enforcement Reports.[11]

[11] The remaining three percent are 2006 and 2007 recalls that were matched to an Enforcement Report, but the information in the Enforcement Report was incomplete.

The number of recalls with missing classification information is greatest in 2009 and accounts for 43 percent of all missing observations. However, 2009 was an exceptional year with a staggering 888 recalls overseen by the FDA; therefore, one possible explanation for the missing Enforcement Report entries may have been limited and strained FDA resources.

Table 7. Total Number of Food Product Recall Events by Class and Year, 2004-2013

Class	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total
I	202	175	116	170	183	603	336	318	367	236	2,706
II	58	65	70	79	70	116	153	229	276	233	1,349
III	33	30	35	38	38	33	35	57	63	57	419
Missing	57	31	27	33	25	212	22	23	52	11	493

Note: The total number of food recall events by severity classification exceeds the total number of food recall events in Table 1 because 64 recall event include products in at least two different severity classifications.

Table 7 reveals that the number of Class II and Class III recall events increased steadily throughout the decade, and we can again compare averages from the first five years to the last five years to determine whether any differences are statistically significant. These averages, presented in table 8, indicate that indeed the number of Class I, II, and III recall events were significantly greater in the latter half of the decade than the former, particularly the number of Class II recalls.

Table 8. Average Number of Annual Food Product Recall Events by Class, 2004-2013

Class	Average 2004-2013	Average 2004-2008	Average 2009-2013
I	270.6	169.2	372*
II	134.9	68.4	201.4**
III	41.9	34.8	49.0*
Missing	49.3	34.6	64.0

Note: Asterisk (*) and double asterisk (**) indicate that the *t*-test of a difference in the means for 2004 to 2008 and 2009 to 2013 is significant at the five and one percent level, respectively.

To determine whether some foods are inherently riskier than others and thereby the subject of more Class I recalls as compared to Class II or III recalls, figure 9 charts the share of Class I, II, and III recalls for ten aggregate food categories. Between 2004 and 2013, nut products, when recalled, were more likely to be classified as Class I recalls as compared to other food categories. This suggests that when nuts, nut mixes, nut butters, and other nut products are the subject of a recall, they present a greater health risk to the general public. Conversely, foods categorized as grains or "other food products" were more likely to be classified as Class II or Class III as compared to other food categories, suggesting these foods pose a lesser threat when recalled.

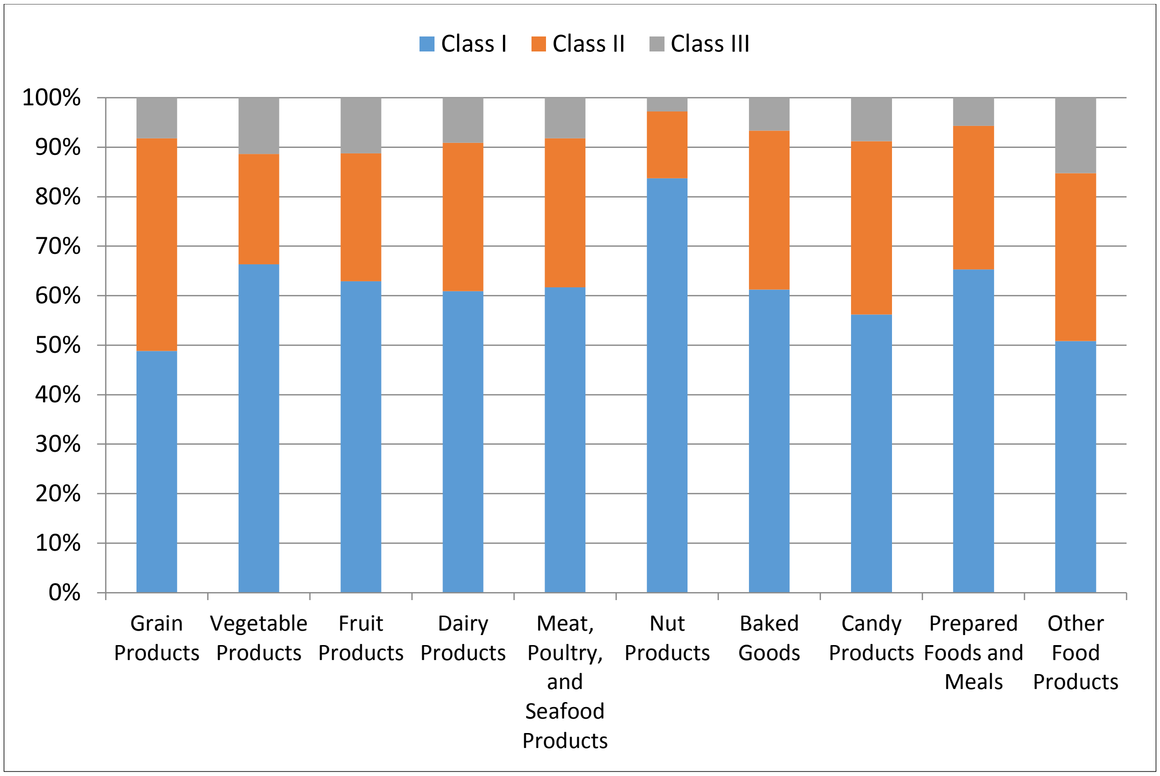

Figure 9. Share of Class I, II, and III Recall Events by Food Type, 2004-2013.
Note: Based on 4,628 observations. 524 observations have a missing risk classification.

Though aggregation of foods into ten major food categories allows one to visually compare general patterns between aggregate categories, trends also exist among the finer, disaggregated categories of Appendix A. For example, for recalled fresh produce with classification information, 80.0 percent of fungi, 83.9 percent of fresh herbs, 84.2 percent of vine-stalk vegetables, 87.5 percent of root vegetables, 91.8 percent of leafy vegetables, 93.5 percent of fruit, and 100 percent of sprouts were classified as Class I recalls. These statistics suggest that fresh produce products, when recalled, present a serious health risk. In contrast, for recalled meat and seafood products with classification information, 14.5 percent or mollusk products, 56.5 percent of crustacean products, 56.7 percent of fish products, 61.5 percent of pork products, 62.9 percent of processed meat products (bacon, sausage, lunch meats, etc.), 73.7 percent of poultry products, and 79.5 percent of beef products were classified as Class I recalls.

Another informative exercise is a review health risks by class to gain insight into which health risks FSIS and FDA deem to be the most severe. Figure 10 plots the share of ten health risks for each severity class for food recall events between 2004 and 2013. Bacterial pathogen contamination (e.g., STEC, *Salmonella, Listeria monocytogenes*, etc.) was almost always deemed a severe threat to public health; comprising 58 percent of all Class I recalls, and only 8 percent of Class II recalls and 4 percent of Class III recalls. Undeclared allergens were also a frequent source of Class I and Class II recalls, comprising 30 percent of Class I recalls and 32 percent of Class II recalls. In contrast, recalls due to undeclared substances, such as sulfites and food coloring, and extraneous material recalls were deemed to be lesser threats to public health as they were most frequently categorized as Class II or III. Recalls due to mislabeling and "other reasons" were deemed the least severe in terms of public health. Together, these recalls comprised the majority of Class III recalls, recalls that present no risk of adverse health consequences from consumption.

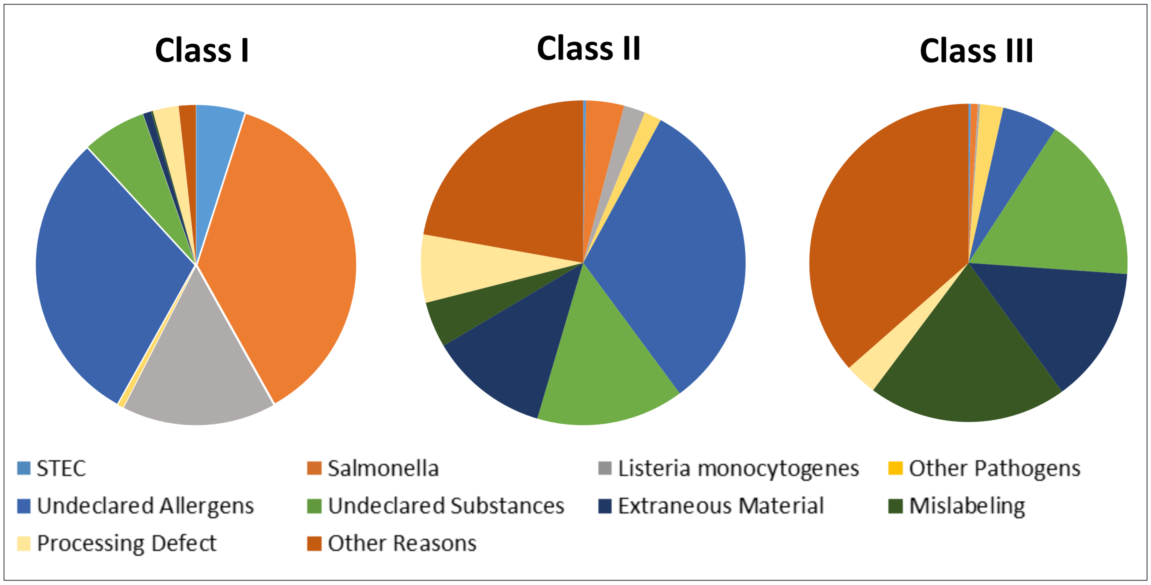

Figure 10. Health Risk Share of Class I, II, and III Recall Events, 2004-2013.
Note: Based on 4,406 observations. 493 observations have a missing risk classification and one observation has missing health risk information.

Recalls by Geographic Distribution

Most recall events are regional in nature. Recalled products are only occasionally distributed nationwide. In fact, between 2004 and 2013, only 25.2 percent of recall events included products intended for nationwide distribution.[12] The remaining recall events included products distributed to regions identified in the FDA or FSIS press releases or FDA Enforcement Reports. The size of the distribution area ranged from a single city or county to dozens of states, and the average regional recall impacted five states.[13]

Figure 11 maps the distribution of recalled products in the contiguous United States between 2004 and 2013. New York, California, Texas, Illinois, Pennsylvania, and

[12] Geographic distribution is missing for 88 (1.8 percent) recall events.
[13] As mentioned in the text, FDA Enforcement Reports were used to verify the information contained within FDA press releases. Sometimes, however, there was conflicting information regarding geographic distribution in the FDA Enforcement Reports and FDA press releases. Of the 4,254 FDA recalls, 377 (8.8 percent) had conflicting geographic information. In these cases, the geographic information from the press releases was used. For FDA recalls without press releases, geographic information from the Enforcement Reports was used.

Florida received the greatest number of recalled products. This was expected given that these are also the six most populous states, and therefore, receive and consume the greatest volume of food in the United States.

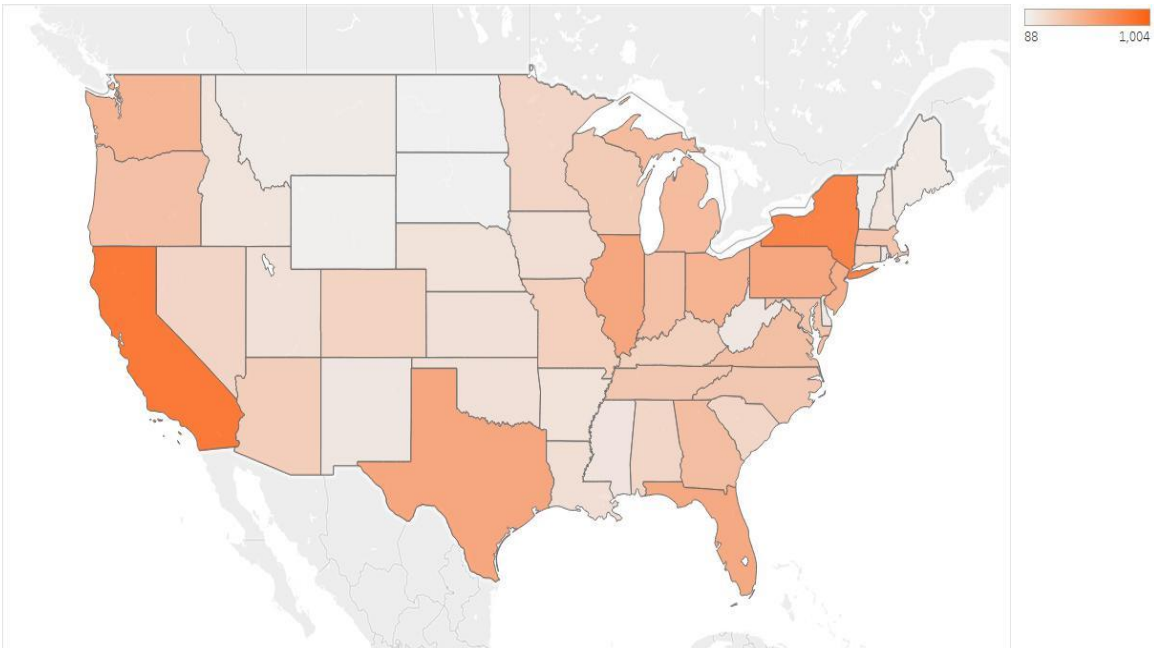

Figure 11. Geographic Distribution of Recalled Products, 2004-2013.
Note: Based on 3,558 observations. 1,213 observations were nationwide, 41 observations had other geographic designations (e.g., Northeast, West Coast, etc.), and 88 observations had missing geographic information.

Discussion

Food product recall events increased by an average of 45 events a year between the years 2004 and 2013. An increasingly complex food supply system, technology improvements in health risk detection, increased regulatory oversight and enforcement, and the passing of two major food policy laws (FALCPA and FSMA) all likely contributed to the significant rise in food product recalls. By breaking down and examining trends and patterns, we can further pinpoint driving factors and form educated hypotheses behind the overall increase in food product recalls. Thus, the primary objective of this study was to analyze recall events over time by the types of foods recalled, the health risks involved, the severity of the health risks, and the geographic distribution of recalled products. Identification of any patterns and trends can provide guidance for manufacturer best practices and targets for regulatory oversight. Moreover, an analysis of this sort, that considers both FDA and FSIS recalls, has not previously been completed and fills an important void in the literature.

The results reveal that recall events increased across several major aggregate food categories, increased across all three severity classes (particularly Class II), and occurred more frequently in population-dense areas. Additionally, the results highlight several major recent trends. The first is the potential magnitude and impact of ingredient-driven recall events, the source of several extreme time trend outliers, including peanut butter, pistachios, and HVP. Recalls of upstream ingredients can expand exponentially and impact dozens, if not hundreds, of downstream users of the implicated ingredients. Between 2004 and 2013, 22 percent of all recalls were the result of an upstream ingredient being recalled first. The widespread impact of these expanded recall events suggests that high-risk ingredients that are shipped to multiple manufacturers through various marketing channels for consumption in various settings may require greater oversight to prevent disastrous ripple effects for downstream manufacturers.

Another major insight from the analysis was the significant growth in the total number of prepared meal recall events and meat, poultry, and seafood product recall events. Interestingly, the safety of these goods falls under the authority of both FDA and FSIS. For animal products, FDA oversees the safety of seafood products and FSIS oversees the safety of meat and poultry products. For prepared meals, FDA oversees the safety of prepared meals without meat and poultry and FSIS oversees the safety of prepared meals with meat and poultry. For example, a frozen pizza with mushrooms falls under the federal authority of FDA, while a frozen pizza with pepperoni falls under the federal authority of FSIS. The significant increase in the total number of prepared meal recall events and meat, poultry, and seafood product recall events may be an example and consequence of the inherent inefficiencies of this bifurcated system and may provide further rationale for a broad restructuring of the nation's food safety oversight.

Lastly, the final major insight from the analysis is the overwhelming increase in the number of recalls due to undeclared allergens. Between 2004 and 2013, undeclared allergens were the leading cause of food product recall events, accounting for 27 percent of all recall events. Accurately labeling allergens is vital for public health, especially for the public health of children under the age of 18. Four out of every one hundred children in United States reports having a food allergy, and the prevalence of reported food allergies is only increasing. Effective in 2006, FALCPA requires that all eight major food allergens (wheat, eggs, peanuts, milk, tree nuts, soybeans, fish, and crustacean shellfish) be properly labeled on food products. Thus, FALCPA likely played a major role in the dramatic increase in the number of undeclared allergen recalls. Future work monitoring undeclared allergen recalls is needed to determine whether the total number of recalls continues to increase or whether the observed increase was part of an industry adjustment period as manufacturers adjusted to the requirements of FALCPA. In any case, in contrast to pathogen contamination, which did not cause a significant increase in the total number of recall events, undeclared allergens are largely a labeling issue because unlabeled food products only pose health risks to individuals with allergies. Given the massive expense recalls present, this finding suggests that more time and effort should be spent reviewing labels to ensure they are accurately labeled prior to sale.

In all, food product recall events have significant impacts for both producers and consumers. For producers, recalls represent a massive expense that can potentially bankrupt manufacturers. For consumers, recalls signal unsafe foods, and concerns of foodborne disease can potentially influence consumer demand. Given the increasing number of recall events and the substantial direct and indirect costs of recalls on producers, consumers, and regulators, there is a fundamental need to identify and understand trends, such as the ripple effects of ingredient-driven recall events, the increase in animal product recalls, and the increase in undeclared allergen recalls. These insights can provide guidance for manufacturer and regulator efforts, and potentially lead to a reduction in excessive recall costs and improve the overall quality and safety of the food supply.

II. Impact of Food Safety Information on Consumer Demand: Literature

The market for food safety is characterized by imperfect information. Therefore, consumers must assess the safety of a product based on their personal experiences and external signals relaying information about relative health risks. How consumers respond to food safety information can have significant industry implications, and therefore, is of great interest to producers, commodity organizations, and policy makers. That is, changes in consumer behavior in response to food safety risks can provide insight into the value consumers place on food safety and provide justification for increased food safety measures. However, there is still considerable heterogeneity as to how to best study the impact of food safety information on consumer demand.

Over the past several decades, an extensive and growing body of literature empirically estimating the impact of food safety information on the demand for food products has emerged.[14] These studies can usually be classified into one or more of three groups: studies that use continuous-time food safety media indices, studies that analyze the impact of a single food safety event, and studies that use data aggregated across consumers and across time. While each of these methods has its advantages and disadvantages, the conclusions are general similar. Most studies have concluded that food safety information has a significant effect on consumer demand, though the effect is often marginal and short-term.

[14] While this section focuses on food safety information, there is also a broader literature on the impact of general product safety information. Specifically concerned with the impact of non-food product recalls, Crafton, Hoffer, and Reilly (1981) investigated the impact of automobile recalls, Cawley and Rizzo (2008) examined the impact pharmaceutical recalls, and Freedman, Kearney, and Lederman (2012) estimated the impact of toy recalls.

Historically, analysis of food safety media indices – indices constructed based on the number of published articles pertaining to food safety and product contamination over a specified time frame – has been the most popular strategy in investigating the impact of food safety information. Smith, van Ravenswaay, and Thompson (1988) concluded that media publicity following the 1982 heptachlor contamination of fresh milk in Oahu, Hawaii had a significant negative effect on aggregate monthly milk purchases. Brown and Schrader (1990) found that information linking cholesterol and heart disease decreased per capita shell egg consumption by 16 to 25 percent by the first quarter of 1987.[15] Similarly, using the same index data as Brown and Schrader, Kinnucan et al. (1997) found that beef demand decreased with the dissemination of cholesterol-related health information, while poultry demand increased and pork and fish demand remained unaffected. Burton and Young (1996) observed that media publicity of bovine spongiform encephalopathy [BSE] in Great Britain had a significant effect on consumer meat expenditures, with the market share for beef declining by 4.5 percent by the end of 1993. Dahlgran and Fairchild (2002) concluded that adverse publicity regarding *Salmonella* depressed the demand for poultry, though the magnitude of the effect was small, less than one percent, with consumers reverting back to previous consumption behavior in several weeks. Piggott and Marsh (2004), using multiple meat-specific media indices for beef, pork, and poultry, found that the average demand response was small, though statistically significant, in the short-run and there was no lasting effect in the long-run. Lastly, analyzing disaggregated household panel data collected by the National

[15] However, rather than using a typical newspaper media index, the authors constructed a lagged index based on the number of published relevant medical journal articles as a proxy for information reaching consumers.

Purchase Diary Group, Coffey, Schroeder, and Marsh (2011) also studied the impact of food safety media indices. Similar to the methods of Piggott and Marsh, Coffey et al. created several meat-specific media indices to estimate the effect of media on 12 different conventional beef, pork, poultry, and fish products. Ultimately, they found the food safety media index elasticities to be small, and for the most part, not significant. The one exception was the elasticity of pork chops with respect to the pork food safety index.

The use of media indices, however, limits analyses in that it does not necessarily capture the effect of actual food safety events on consumer demand. For one, the use of media indices often implicitly assumes that consumers nationwide are equally affected by the same media information, thereby effectively diminishing any impact of a localized food safety event on local consumers. Secondly, consumers may perceive media reports to be a source of biased information regarding food quality, whereas actual food safety events may be perceived as a source of unbiased information. Thus, depending on the direction of the bias, media indices could potentially understate or overstate any impact on consumer demand. Along these lines, media reports may be positive (e.g., reports on improvements in food safety technology) or negative (e.g. reports on a foodborne illness outbreak) and determining whether a media report is positive or negative may be difficult to automate. Therefore, construction of indices can often be extemporaneous and noisy. Lastly, as Marsh, Schroeder, and Mintert (2004) acknowledged, there are likely diminishing returns to multiple media reports on a single event; therefore, media indices could again underestimate any impact of food safety information on consumer demand.

Alternatively, other studies have analyzed the impact of a single food safety event on consumer demand. Foster and Just (1989) measured the consumer welfare loss due to nondisclosure of information following the 1982 heptachlor contaminated milk crisis in Hawaii using the same aggregate consumption data as Smith, van Ravenswaay, and Thompson. In doing so, they first demonstrated using a dummy variable approach that the crisis had a sizable and significant negative impact on milk consumption. Shimshack, Ward, and Beatty (2007) examined responses to a national FDA advisory urging at-risk consumers (i.e., households with young children, nursing mothers, and pregnant women) to limit store-bought fish consumption due to possible methyl-mercury exposure. Analyzing disaggregated household panel data and employing both parametric and non-parametric methods, they found that some targeted consumers significantly reduced canned fish purchases as a result of the advisory. Schlenker and Villa-Boas (2009) estimated the consumer response following the first discovery of BSE in the United States in December 2003 and observed a significant and robust drop in beef purchases using product-level scanner panel data from one of the largest national grocery store chains. Lastly, Bakhtavoryan, Capps, and Salin (2014) empirically estimated the impact of a 2007 Peter Pan peanut butter recall and found a significant negative impact on the demand for the implicated brand and a positive spillover effect for the leading competitor brand. Nonetheless, studies such as these, which focus on a single unique food safety event, may not accurately represent the impact of recurrent food safety events, such as recalls, which occur continuously throughout the year.

To address these shortcomings, Marsh, Schroeder, and Mintert (2004) analyzed the impact of meat product recalls on consumer demand. In doing so, the authors argued that consumers perceive recall events as an unbiased proxy for low quality. Furthermore, they conducted the same analysis with media indices instead of recalls to determine any differences in strategy. Their results indicated that recall events indeed significantly impacted aggregate demand for meat products, while media reports did not. Similarly, Tonsor, Mintert, and Schroeder (2010) also examined the impact of recalls on aggregate quarterly demand for meat products. They concluded that a 10 percent increase in beef recalls reduced aggregate beef demand by 0.2 percent and increased poultry demand by 0.2 percent in the long run. Most recently, Taylor, Klaiber, and Kuchler (2016) analyzed the impact of ground beef recalls on consumer demand with disaggregated household purchasing data and determined that ground beef recalls had no impact on household purchases of ground beef prior to the discover of BSE in the United States. However, following the 2003 BSE discovery event, the average impact of a ground beef recall was a 0.26 pound per person reduction in retail purchases.

It must be noted that the majority of the mentioned studies used data aggregated across consumers and across time. However, aggregation of data across households reduces the amount of information available from demand analysis by ignoring variability in purchasing behavior among households. For example, any income measure included in a demand analysis using linearly aggregated data implicitly assumes that income is evenly distributed across households. If this unrealistic assumption is not met, the aggregate demand function will not represent the individual household function and parameter estimates will likely be biased (Mittelhammer, Shi, and Wahl 1996). Additionally, aggregation of data across time, e.g., quarters or years, further reduces the informativeness of demand analysis by ignoring or diminishing any short-run impact that may occur in the weeks immediately following the recall.

To improve upon and contribute to the existing literature, Chapters IV and V analyze disaggregated household panel data and multiple food safety events that vary both temporally and geographically. As outlined above, previous studies investigating the impact of food safety information on consumer demand have relied heavily upon analyses of media indices, singular events, or aggregate data. However, analyses of media indices and singular events do not necessarily capture the impact of actualized recurrent food safety events, and analyses of data that have been aggregated across households and across time often ignore household heterogeneity, localized impacts of regional events, and any immediate short-run effects. In contrast, the case studies presented in the final chapters analyze disaggregated household data to estimate the impact of multiple clearly delineated recall events that vary over time and space. First, however, to motivate the empirical analyses, the subsequent chapter develops a Bayesian theoretical framework to illustrate how consumers may respond to negative information signals.

III. Recalls and Consumer Perception of Risk: A Theoretical Framework

Food purchase decisions are largely determined by a consumer's knowledge of product attributes. Sometimes, consumers have perfect information prior to purchase, such is the case for appearance attributes. For other attributes, commonly referred to as experience attributes, information is only obtained after purchase, for example, taste. And lastly, for other attributes, referred to as credence attributes, information cannot be determined or confirmed even after purchase, such as nutrition and health claims. In the ideal case of complete perfect information, markets function efficiently. Consumers purchase products they demand at the minimum average cost of production. Often, however, consumers have imperfect information and must make purchase decisions under uncertainty, which can lead to market failure. Such is the case with food safety, which can be characterized either as an experience or credence good. Food safety is an experience good if a consumed food causes an acute illness that can be traced back to a specific food source with certainty. More often than not, however, food safety is a credence good because delayed reactions hinder efforts to trace back and identify the specific source of any discomfort or illness. In some markets, to remedy the imbalance of information between producers and consumers, third-party providers can certify and disclose quality through certification programs (Dranove and Jin 2010). However, in many food markets, there are very few, if any, providers that disclose systematic food safety information through certification programs. Often, the only instance when consumers are informed of product safety is when a product's quality falls below a certain threshold, for example, when a product is recalled (Freedman, Kearney, and Lederman 2012). Consumers, in turn, may use this information to update their expectations about the quality of other products in the same market.

To fully understand how consumers respond and react to food safety signals, such as product recalls, one must first consider how consumers form perceptions of risk. Do consumers respond to negative signals? How do negative signals impact risk perception? Does the content of the negative information matter? And how do consumers perceptions of risk impact purchasing decisions? Answers to these questions are useful for motivating empirical analyses assessing the impact of food safety information on consumer demand. The objective of the following framework is to model the process by which consumers translate new information into risk, and in turn, how perceptions of risk impact demand.

Risk Perception Development

Consumers derive value from food safety because it signals a lower degree of health risk. Yet consumers often face imperfect information; that is, they are mostly uncertain regarding the safety of available food products. If a consumer had perfect information, the safety of the food product would be no different than other quality attributes, such as taste, appearance, source, etc. And the consumer would make a purchase decision based on his or her preferences, income, and price of the product. Without perfect information, however, consumers must assess a food product's safety based on their personal experience and communications. Often, when purchases are supported by satisfactory experiences, a consumer will form routine shopping behaviors (Hoyer 1984). Established routine purchases will continue until the consumer receives a signal strong enough to revise prior risk perceptions and decision rules.

The learning process by which consumers process information and update their risk perceptions can be expressed with a Bayesian revision process (see Viscusi and O'Conner 1984; Viscusi 1989; Liu et al. 1998; Böcker and Hanf 2000). Following Viscusi (1989) and Liu et al. (1998), let r_t denote perceived risk, i.e., the perceived probability that a given good is unsafe at time t, and let s_t denote a negative information signal on the safety of that good, e.g., a recall. The updated perceived risk (posterior risk) can then be expressed as the weighted average of the prior perceived risk and the sample risk:

$$r_{t+1} = \omega_{t+1} r_t + (1 - \omega_{t+1}) f(s_{t+1}), \tag{1}$$

where $f(\cdot)$ is a function that converts the signal into a sample risk and ω_t is a weight for combining the prior perceived risk and the sample risk. For simplicity, assume no news is good news so that $s_t \geq 0$, $f(s_t = 0) = 0$, and $f(s_t > 0) > 0$. That is, when no signal is observed, the consumer perceives the food product to be safe and the sample risk is zero.[16] The advantage of this Bayesian framework is that it illustrates frequently observed behavior following the release of negative information: an immediate change in behavior, followed by a gradual return to previous, routine behavior. Through a dynamic adjustment process and without any further information shocks, perceived risk eventually returns to initial levels.

How long the return to baseline behavior takes depends on the strength of the negative signal. Stronger signals will inevitably require a longer recovery period than weaker signals, for example, recalls prompted by a consumer illness investigation will

[16] The assumption that consumers may perceive no news as good news is not unfounded. A study of consumer attitudes towards food safety showed that individuals often display 'optimistic bias' and hold an illusion of personal invulnerability with regard to food safety hazards (Redmond and Griffith 2004).

likely require more recovery time than recalls prompted by product testing. To demonstrate this, assume the weight ω is constant throughout time. Suppose the baseline perceived risk is r_0 and there is a negative shock in period 1. Assuming no more shocks, the perceived risk at time T is

$$r_T = \omega^T\left(r_0 + \omega^{-1}(1-\omega)f(s_1)\right). \tag{2}$$

To determine an expression for the length of time to recovery, set $r_0 = r_T$ and solve for T.

$$T = \frac{\ln(r_0) - \ln\left(r_0 + \omega^{-1}(1-\omega)f(s_1)\right)}{\ln(\omega)} \tag{3}$$

Taking the derivative with respect to the signal, s_1, the expression becomes

$$\frac{\partial T}{\partial s_1} = -\frac{(1-\omega)f'(s_1)}{\ln(\omega)\left(\omega r_0 + (1-\omega)f(s_1)\right)}. \tag{4}$$

Assuming $f'(\cdot) > 0$ (stronger signals translate to greater risk) and because $0 < \omega < 1$, then $\partial T/\partial s_1 > 0$. Therefore, stronger negative signals require greater recovery times.

Now consider the possibility of multiple negative signals. Suppose a shock occurs every period between 1 and τ, followed by periods where no shocks are observed between $\tau + 1$ and T ($1 < \tau < T$). The posterior risk perception in time T would then be

$$r_T = \omega^T(r_0 + \textstyle\sum_{t=1}^{\tau} \omega^{-t}\,(1-\omega)f(s_t)). \tag{5}$$

Again, we set $r_0 = r_T$ and solve for T.

$$T = \frac{\ln(r_0) - \ln\left(r_0 + \sum_{t=1}^{\tau} \omega^{-t}(1-\omega)f(s_t)\right)}{\ln(\omega)} \tag{6}$$

Now define τ_2 as a period of time greater than τ_1, and again shocks occur every period between 1 and τ_1 or τ_2. Because $\tau_2 > \tau_1$, then the length of time to recovery following

$\tau_2$shocks, T_2, will be greater than the length of time to recovery following τ_1 shocks, T_1 ; that is, $T_2 - T_1 > 0$. To prove this, assume otherwise: $T_2 - T_1 \leq 0$.

$$\frac{\ln(r_0)-\ln\left(r_0+\sum_{t=1}^{\tau_2}\omega^{-t}(1-\omega)f(s_t)\right)}{\ln(\omega)} - \frac{\ln(r_0)-\ln\left(r_0+\sum_{t=1}^{\tau_1}\omega^{-t}(1-\omega)f(s_t)\right)}{\ln(\omega)} \leq 0$$

$$-\ln\left(r_0 + \sum_{t=1}^{\tau_2}\omega^{-t}(1-\omega)f(s_t)\right) + \ln\left(r_0 + \sum_{t=1}^{\tau_1}\omega^{-t}(1-\omega)f(s_t)\right) \geq 0$$

$$\ln\left(r_0 + \sum_{t=1}^{\tau_2}\omega^{-t}(1-\omega)f(s_t)\right) - \ln\left(r_0 + \sum_{t=1}^{\tau_1}\omega^{-t}(1-\omega)f(s_t)\right) \leq 0$$

$$\sum_{t=1}^{\tau_2}\omega^{-t}(1-\omega)f(s_t) - \sum_{t=1}^{\tau_1}\omega^{-t}(1-\omega)f(s_t) \leq 0$$

$$\sum_{t=\tau_1+1}^{\tau_2}\omega^{-t}(1-\omega)f(s_t) \leq 0$$

This leads to a contradiction because each term in the summation expression is positive: $0 < \omega < 1$ and $f(s_t > 0) > 0$. Therefore, $T_2 - T_1 > 0$, which proves that multiple signals only lengthen the time necessary for recovery. Alternatively, this can be demonstrated by redefining the length of period t to be inclusive of multiple shocks. Multiple shocks in a single period can be interpreted as stronger signals than a single or fewer shocks in a period, and because we've already shown that stronger signals lead to greater recovery times, we can also conclude that, similarly, multiple shocks also lead to greater recovery times.

Demand Impact

Now consider a consumer who derives utility directly from the consumption of good, y, and the quality or safety of that good, q.[17] Assume that the quality of the potentially risky

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[17] Several authors have modeled demand for food safety by including a health function in the theoretical framework, where health in turn is a function of quality and other factors (see van Ravenswaay and Hoehn 1996; Antle 2001). Alternatively, others have modeled demand for food safety by incorporating quality

good, q, has a binary distribution. That is, the product is either contaminated with a harmful pathogen, q^C, or not, q^{NC}. However, as previously stated, although quality enters a consumer's utility function, the exact quality or safety of a particular good is not known to the consumer prior to purchase. The consumer only has formed a perception of risk (the probability that a good is unsafe), previously defined as r. At this stage, several additional standard assumptions are necessary regarding utility. Namely, utility increases with consumption; utility increases with quality; and lastly, consumers are risk-averse and the consumer's utility function is concave with respect to y. Ultimately, the consumer's expected utility, $E[U]$, can be expressed as

$$E[U(y,q)] = (1-r)u(y,q^{NC}) + ru(y,q^C) \tag{7}$$

where $u(\cdot)$ is a sub-utility within the general form. To determine the comparative statistic $\frac{dy}{dr}$, the change in demand in response to a change in perceived risk, we use the implicit function theorem upon calculating the first-order and second-order conditions.

$$\frac{dy}{dr} = \frac{u_y(y,q^{NC}) - u_y(y,q^C)}{(1-r)u(y,q^{NC}) + ru_{yy}(y,q^C)} < 0 \tag{8}$$

Assuming that the marginal utility from a non-contaminated good is greater than the marginal utility of a contaminated good (numerator) and knowing that $u_{yy}(\cdot) < 0$ because utility is concave (denominator), then as perceived risk for a good increases, demand for the good decreases, $\frac{dy}{dr} < 0$. Note that the comparative statistic $\frac{dy}{dr}$ is derived here from a simple one-good utility maximization problem without an income constraint.

directly into the utility framework (see Piggott and Marsh 2004; Coffey et al. 2011). For simplicity, the latter method is applied here.

However, it is also possible to demonstrate a similar result from a two-good (one no-risk good and one risky good) utility maximization problem with an income constraint.

Next, linking food safety signals, s, to demand is straightforward. Applying the chain rule, the relationship becomes

$$\frac{dy_t}{ds_t} = \frac{dy_t}{dr_t}\frac{\partial r_t}{\partial s_t} \tag{9}$$

and because $\frac{dy_t}{dr_t} < 0$ and $\frac{\partial r_t}{\partial s_t} > 0$, then $\frac{dy_t}{ds_t} < 0$. That is, as a consumer receives stronger negative signals thereby increasing perceived risk, the likelihood of purchasing potentially contaminated food products declines. Additionally, we can further deduce that

$$\frac{dy_t}{ds_t} < \frac{dy_{t+1}}{ds_t} < 0. \tag{10}$$

To prove this, assume otherwise: $\frac{dy_t}{ds_t} \geq \frac{dy_{t+1}}{ds_t}$.

$$\frac{dy_t}{dr_{i,t}}\frac{\partial r_{i,t}}{\partial s_{i,t}} \geq \frac{dy_{i,t+1}}{dr_{i,t+1}}\frac{\partial r_{i,t+1}}{\partial r_{i,t}}\frac{\partial r_{i,t}}{\partial s_{i,t}}$$

$$\frac{dy_{i,t}}{dr_{i,t}} \geq \frac{dy_{i,t+1}}{dr_{i,t+1}}\omega$$

Assuming that, all else equal, the change in demand in response to a marginal change in perceived risk does not vary from period to period, that is, $\frac{dy_{i,t}}{dr_{i,t}} = \frac{dy_{i,t+1}}{dr_{i,t+1}}$, then $\omega \geq 0$.

This leads to a clear contradiction because ω is already defined as $0 < \omega < 1$. Therefore, we can conclude that the impact of a negative information signal on demand diminishes over time. Similarly, given the direct link between information signals and demand, we can posit that stronger signals and multiple signals will lead to longer recovery times.

Applications

The theoretical model developed in this chapter establishes the conceptual framework for interpreting empirical estimates of the impact of food safety information on consumer demand. If recall events are in fact negative information signals that consumers use to update their expectations about the safety of food products, we expect consumer demand for the implicated products to decline. We also expect the strength of signal to influence the magnitude of the impact. That is, stronger signals are expected to have greater impacts. Additionally, through a dynamic adjustment process, we expect demand to recover and eventually return to initial consumption levels. The time necessary for recovery is a function of signal strength and the weight consumers place on their own experiences versus new negative information. However, stronger signals are expected to require greater recovery periods. Empirically estimating the impact of food safety information on consumer demand is an informative exercise in order to determine whether these relationships actually hold in reality. Chapter IV analyzes the impact of negative signals on the likelihood of purchasing leafy greens and estimates the time to recovery. Chapter V considers signal strength and analyzes the impact of varying negative signals on the likelihood of purchasing packaged ground beef, and again, estimates the time necessary for recovery.

IV. Demand Impacts of Leafy Green Product Recalls

In September of 2006, leafy green safety made nationwide headlines due to an unprecedentedly large, multi-state *E. coli* O157:H7 outbreak linked to contaminated bagged spinach. In all, the outbreak resulted in 204 known illnesses, 104 hospitalizations, and three deaths. While the 2006 spinach outbreak is a dramatic example of a food safety incident involving leafy greens, bacterial contamination cases continue to occur on a regular basis, albeit on a smaller scale. In fact, using data from outbreak-associated illnesses from 1998 to 2008, the CDC recently determined that more foodborne illnesses were attributed to leafy vegetables (22 percent) than to any other commodity, including meat, poultry, dairy, and eggs (Painter et al. 2013).

The increasing prevalence and prominence of incidents of foodborne illness linked to leafy greens has the strong potential to undermine consumer confidence in the national supply of leafy greens, especially packaged and bagged leafy green products. Since the spinach contamination event of 2006, several authors have investigated the impact of the outbreak on leafy green demand. Arnade, Calvin, and Kuchler (2009), using aggregate expenditure data for spinach, bagged salads, and other leafy greens, showed that the 2006 spinach recall led to a substantial decrease in purchases of bagged spinach and a marginal decrease in purchases of bulk spinach, with impacts persisting for over a year. Additionally, their results indicated that bulk lettuces served as shock substitutes as consumers purchased fewer spinach products and more bulk lettuces of all types in response to the recall. Similarly, Arnade, Kuchler, and Calvin (2011), using an error correction model to estimate the rate of adjustment from disequilibrium after the shock to equilibrium, found that it took consumers 8.5 weeks to return to the equilibrium for bagged spinach demand.

Inevitably, concerns of bacterial contamination and foodborne disease can significantly influence demand for leafy green products. As demonstrated in Chapter III, recalls may serve as external signals relaying information to consumers about relative health risk. That is, following a leafy green recall event, perceived risk of bacterial contamination may be particularly heightened if consumers interpret recall events to be an unbiased proxy for low quality (as suggested by Marsh, Schroeder, and Mintert 2004). The primary objective of this research is to investigate the effect of food safety recalls on the demand for leafy green products. The proposed present study contributes to the leafy green demand literature, and the food safety literature overall, by analyzing disaggregated household-level data to estimate the effect of multiple leafy green recall events that vary over time and space. By using disaggregated household demographic and purchasing data, this study effectively takes advantage of the geographic and temporal variability of leafy green product recalls in order to accurately measure the impact of multiple food safety signals on the demand for leafy green products. That is, temporal variability allows for the analysis of multiple recall events over time, and geographic variability allows for the analysis of a regional recall on the impacted region as compared to the rest of the nation.

Leafy Green Recall Data

Information about leafy green recall events was gathered from both FDA press releases and FDA Enforcement Reports, discussed in greater detail in Chapter I. As this study is primarily concerned with household purchases of retail goods in response to recalls, only publicized food recalls are considered (i.e., recalls with press releases), and Enforcement Reports are used to verify the information contained in the corresponding press releases.[18]

The present study focuses on the years 2008 to 2012, and during those five years, there were over 2,500 food product recall events overseen by the FDA; 41 of which were leafy green (iceberg, romaine, and spinach) recall events due to microbial contamination. Of these 41 recall events, 32 were publicized with a press release. Details of these recall events are summarized in table 9. The most common microbial pathogens associated with these recalls were *Listeria monocytogenes* (44 percent) and *Salmonella* (38 percent); however, other pathogens include *E. coli* O157:H7 (16 percent) and *E. coli* O145 (3 percent).

Table 9. Summary Statistics of Leafy Green Recalls, 2008-2012

	2008	2009	2010	2011	2012	Total
Leafy Green Recall Events	0	3	6	11	12	32
Nationwide Leafy Green Recall Events	0	1	0	0	1	2
Leafy Green Recall Events Linked to a Consumer Illness	0	0	1	0	0	1
Romaine Lettuce Recalls	0	1	3	5	9	18
Iceberg Lettuce Recalls	0	0	0	2	1	3
Spinach Recalls	0	2	3	7	3	15

As previously emphasized, the greatest advantage of using multiple recall events to measure the impact of food safety information is the temporal and geographic variability. Of the 32 leafy green recall events between 2008 and 2012, only two events

[18] As a sensitivity check, the impact of non-publicized recalls on the demand for leafy greens was estimated and found to be largely insignificant. These results are presented in Appendix B.

included leafy green products that were distributed nationwide. The remaining recall events included products that were distributed to regions identified by the firm and FDA in the press release, and the size of the affected regions ranged from a single city or county to several states. Specifically, the average regional recall impacted 11 states, while the most expansive regional recall impacted 26 states.

Household Demographic and Purchasing Data

The primary dataset used in this analysis is the IRI Consumer Network™ - a nationwide panel of households that provide a detailed account of their retail food purchases. The panel is selected to be geographically and demographically representative of the contiguous United States. Households participating in the panel download a mobile application or are provided with a handheld scanner to scan the Universal Product Code (UPC) on all their purchases and upload all information through the Internet. Because household participation and commitment to the panel varies, IRI determines whether to include a household in the *static* panel based on specific criteria. The static panel only includes households that reported purchases at least once every four weeks for 80 percent of the year (11 of 13 four-week periods) and reported average weekly expenditures of 25 dollars for one member households, 35 dollars for two member households, and 45 dollars for three or more member households. The present analysis only considers households in the static panel, and between 2008 and 2012, 106,718 static households participated.

The data of household leafy green purchases include a detailed product description, product brand, leafy green type, date of purchase, total quantity, and total expenditure for every item purchased. Households also provide demographic data including county of residence, household composition, household size, income, education, age, and race. In preparing the static datasets for 2008 through 2012, IRI included only the most recent values for household demographics because its practice is to overwrite household variables as more recent data become available. Consequently, the demographics file contains a snapshot of household characteristics from 2012 or the last year each household reported demographic data, meaning these variables are time-invariant. More information on the technical properties of the IRI data are presented by Muth et al. (2016).

To facilitate the analysis, several specifications were made. First, the products chosen for analysis were packaged leafy green products, specifically romaine lettuce, iceberg lettuce, and spinach.[19] Static households participating in the IRI Consumer Network only record purchases of uniform-weight products and do not record purchases of bulk, random-weight products. However, in November of 2011, a subset of households began recording total expenditures on random-weight products, including random-weight lettuce and spinach.[20] Though it is not possible to consider the impact of leafy green recalls on random-weight purchases from 2008 to 2012, it is possible to compare trends in household expenditures on random-weight and uniform-weight leafy green purchases for 2012 and 2013. For that subset of households, figure 12 plots total monthly

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[19] In greater detail, the products chosen for analysis are packaged iceberg and iceberg-based products (iceberg with shredded cabbage and/or carrot), romaine and romaine-based products (romaine with shredded cabbage and/or carrot), spinach and spinach-based products (spinach with shredded cabbage and/or carrot). Leafy green products containing dressing, toppings (croutons, nuts, berries, etc.), and other vegetables were not considered for analysis.

[20] Participating households chose from a list of products in their mobile application or scanned a bar code on a reference card to record product type and entered total expenditures. Households did not record quantities, which limits the usefulness of the data in food economics research. For more information, see Muth et al. (2016).

expenditures on random-weight and uniform-weight leafy greens for 2012 and 2013. Uniform-weight lettuce accounted for over 70 percent of the lettuce market and, for those two years, uniform-weight and random-weight lettuce expenditures appear to be strongly correlated. Additionally, uniform-weight spinach accounted for a very large share, 85 percent, of the spinach market. Therefore, despite exclusively focusing our analysis on uniform-weight leafy green purchases, we were still able to capture the majority of the impact of leafy green recall events.

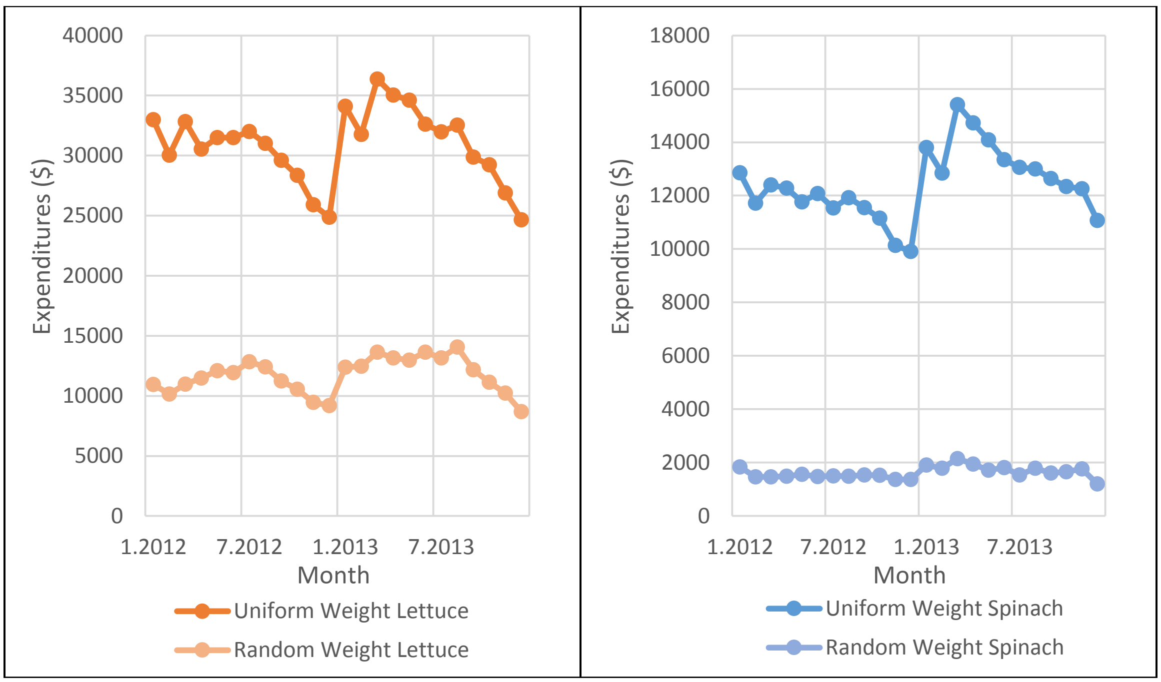

Figure 12. Total Monthly Expenditures on Random Weight and Uniform Weight Leafy Green Products, 2012-2013.
Data: Random Weight Static Households, IRI Consumer Network.[21]

Second, a monthly periodicity was chosen based on frequency of purchase. Of households that purchased leafy green products within a surveyed year, the average

[21] In 2012, 33,854 households participated in the random-weight consumer panel. In 2013, 36,529 households participated. Also, uniform-weight lettuce includes only romaine and iceberg lettuce varieties, whereas random-weight lettuce includes all lettuce varieties.

number of leafy green products purchased was 10. Moreover, of households that purchased a leafy green product within a surveyed month, 53 percent purchased only one leafy green product within that month. This percentage increases when we disaggregate by type of leafy green: romaine (74 percent), iceberg (69 percent), and spinach (78 percent).[22] Given that the majority of households that purchased a leafy green within a given month only purchased leafy greens once, a monthly periodicity is justifiable. Additionally, if a household recorded no purchases in a given month, leafy green or otherwise, the month was omitted from analysis.

Third, only households that purchased a packaged leafy green product at least once during the surveyed period were considered. By only analyzing the consumption patterns of these households, we focus our attention on households that were the most likely to be impacted by leafy green recall events. Thus, the final dataset was reduced from 106,718 static households to 94,763 households. Summary statistics of selected characteristics of participating households as compared to the full IRI panel and Census figures are presented in table 10. The households selected for analysis had an average number of persons per household of 2.50,[23] slightly lower than 2.61, the national average household size estimated by the Census Bureau. Households also had a median annual income range of 50,000 to 59,999 dollars, consistent with the Census Bureau statistic of

[22] A biweekly periodicity was also considered and implemented, increasing the number of time periods from 60 to 130; however, the results did not significantly differ from the results of a monthly periodicity.
[23] Mean household size may be biased downwards because the number of reported individuals per household is capped at eight. However, households of eight or more members only account for 0.41 percent of households in the final panel.

median household income, $53,046.[24] And lastly, 24.5 percent of selected households included an individual under the age of 18.

Table 10. Selected Demographic Distributions from the IRI Consumer Network (%)

	Census[a]	Full IRI Static Panel	Final Panel Dataset
Household Size			
1	27.5	23.0	21.6
2	33.5	41.2	42.0
3	15.9	14.5	14.7
4		12.7	12.9
5		5.4	5.5
6	23.2	2.1	2.1
7		0.7	0.7
8+		0.4	0.4
Household Income			
$0-$14,999	12.6	6.9	6.3
$15,000-$24,999	10.7	9.7	9.1
$25,000-$34,999	10.4	12.6	12.2
$35,000-$49,999	13.7	17.6	17.5
$50,000-$59,999		10.3	10.4
$60,000-$69,999	30.4	8.1	8.3
$70,000-$99,999		19.7	20.3
$100,000+	22.2	15.2	15.9
Presence of Children			
Children under 18	32.8	24.2	24.5
No children under 18	67.2	75.8	75.5
No. of Households	115,226,802	106,718	94,763

[a] Source: U.S. Census Bureau, 2008-2012 American Community Survey 5-Year Estimates

Fourth, and lastly, the analysis could not depend on observed prices alone. That is, if a household chose not to purchase a product, the price they faced for that product was not recorded. Therefore, the average regional price from store-sales data was calculated for each of the 73 IRI-defined markets: 65 major markets (e.g., Los Angeles,

[24] Household income is reported by IRI as a categorical variable, not a continuous variable.

CA; Chicago, IL; Boston, MA; etc.) and 8 larger market areas (e.g., Northeast, Plains, etc.).[25] When available, IRI assigns prices to each UPC-level transaction using its weekly point-of-sale data for the store chain or outlet type and market area. These data were used to calculate price per ounce of leafy greens (romaine, iceberg, and spinach) by dividing total expenditure (dollars) by total quantity (ounces). These average retail regional prices were then used in our model specifications. Table 11 summarizes and compares average retail regional prices with observed prices.

Table 11. Summary Statistics of Observed and Average Regional Prices for Leafy Greens

	No. of Observations	Mean Price ($/oz.)	Standard Deviation
Romaine Lettuce			
Observed	393,738	0.202	0.084
Regional Average	3,304,989 [a]	0.219	0.022
Iceberg Lettuce			
Observed	458,203	0.134	0.068
Regional Average	3,305,078	0.145	0.022
Spinach			
Observed	255,806	0.327	0.168
Regional Average	3,304,154 [a]	0.351	0.042

[a] The total number of household month observations is 3,305,078. The average regional retail prices for romaine and spinach are not complete because the price for romaine was not available for the Boise, ID market in December 2008 and prices for spinach were not available for the Spokane, WA market in October 2008; Boise, ID market in July and August 2008; and the Tulsa, OK market in February, April, June, and August 2008. As no leafy green products were recalled in 2008, these missing price observations should not significantly impact results.

[25] Each household and transaction is assigned to only one IRI-defined market; therefore, a household in Boston, MA would be assigned to the Boston market and not the Northeast market.

Empirical Estimation

Together, the disaggregated household IRI panel data and FDA leafy green recall data allowed for a unique panel estimation of the impact of food safety information on household leafy green demand. The exact empirical strategy was twofold: an estimation of both within household variation over time and between household variation of impacted and non-impacted regions. Explicitly, the identification strategy measured the difference in household purchasing behavior before, during, and after a recall event, and measured the difference in purchasing behavior between households residing in areas impacted by a recall advisory and households residing in the rest of the nation. Motivation and predictions for the empirical analysis are outlined by the theoretical framework of a utility maximizing consumer facing risk uncertainty in Chapter III.

Given the food safety context, demand was estimated using a binary response model. An analysis of food safety events warrants this choice because a household that deems a food product to be risky will be less likely to purchase that product, not decide to purchase but purchase a lesser quantity. In other words, the analysis focuses on the qualitative decision of whether or not to purchase leafy greens rather than the quantitative decision of how much to purchase (given that the household has already decided to buy). The general formulation of a binary response model can be expressed as

$$Y_{h,t}^{*} = \boldsymbol{X}_{h,t}\boldsymbol{\beta} + c_h + \varepsilon_{h,t}$$

$$Y_{h,t} = \begin{cases} 1 & \text{if } Y_{h,t}^{*} > 0 \\ 0 & \text{if } Y_{h,t}^{*} \leq 0 \end{cases} \qquad (11)$$

where $Y^*_{h,t}$ is the latent variable, $Y_{h,t}$ is the observed counterpart (either a value of 1 or 0), $\boldsymbol{X}_{h,t}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, c_h is an unobserved household effect, and $\varepsilon_{h,t}$ is the residual error term.

Multiple methods to estimate binary response models for panel data have been tried and tested. The simplest method is to estimate a linear probability [LP] model with robust clustered standard errors, where

$$\Pr\left(Y_{h,t} = 1 \middle| \boldsymbol{X}_{h,t}, c_h\right) = E\left(Y_{h,t} \middle| \boldsymbol{X}_{h,t}, c_h; \boldsymbol{\beta}\right) = \boldsymbol{X}_{h,t}\boldsymbol{\beta} + c_h. \quad (12)$$

[26]

However, disadvantages of the LP model include that the predicted values of the dependent variable, $\hat{Y}_{h,t}$, may be outside the range of 0 to 1, and it imposes a linear relationship between the dependent variables and the independent explanatory variables. Perhaps the greatest advantage, though, is that the LP model is easy to estimate and easy to interpret. The marginal effects are simply the estimated coefficients, $\boldsymbol{\beta}$.

Alternative nonlinear models that address the disadvantages of LP model are the traditional random effects [RE] probit model and the conditional fixed effects [FE] logit model.[27] The RE probit model, where

$$\Pr\left(Y_{h,t} = 1 \middle| \boldsymbol{X}_{h,t}, c_h\right) = \Phi\left(\boldsymbol{X}_{h,t}\boldsymbol{\beta} + c_h\right), \quad (13)$$

assumes $\boldsymbol{X}_{h,t}$ and c_h are independent, $\boldsymbol{X}_{h,t}$ are strictly exogenous, c_h has a normal distribution with zero mean and variance σ_c^2, and $Y_{h,1}, \dots, Y_{h,T}$ are independent conditional on $\left(\boldsymbol{X}_{h,t}, c_h\right)$. The advantage of an RE probit model over a simple pooled probit model (where the unobservable household effect, c_h, is ignored) is that the RE model allows for

[26] Equation (12) includes household fixed effects, but we also estimated the LP model with time-invariant demographic variables instead of household fixed effects.
[27] Though one might also consider estimating a fixed effects probit model so as not to make any unrealistic assumptions regarding unobservable household effects, traditional nonlinear fixed-effects maximum likelihood estimation yields inconsistent results due to the incidental parameters problem.

serial correlation in the unobserved factors determining $Y_{h,t}$, i.e., $c_h$and $\varepsilon_{h,t}$. Another advantage of the RE model is that it is subsequently possible to calculate average partial effects.

The FE logit model, where

$$\Pr\left(Y_{h,t} = 1 \middle| \boldsymbol{X}_{h,t}, c_h\right) = \Lambda\left(\boldsymbol{X}_{h,t}\boldsymbol{\beta} + c_h\right), \tag{14}$$

relaxes a few of the assumptions necessary for the RE probit model. Specifically, it makes no assumptions about the distribution and relation of c_h to $\boldsymbol{X}_{h,t}$. In other words, it is possible to obtain consistent estimates of $\boldsymbol{\beta}$ regardless of how c_h and $\boldsymbol{X}_{h,t}$ are correlated, an important advantage over the RE probit model, which assumes $\boldsymbol{X}_{h,t}$ and c_h are independent. This is possible because the logit functional form enables us to eliminate c_h from the estimating equation (see Wooldridge 2002, p. 490-492 for greater detail). However, because we eliminate and do no obtain estimates of c_h alongside $\boldsymbol{\beta}$, we cannot estimate average partial effects, a clear disadvantage, though we are able to estimate odds ratios. Another disadvantage is that in addition to c_h being eliminated from the model, any other time-invariant variables are also eliminated. And lastly, households for which the binary dependent variable is equal to 0 for every time period or equal to 1 for every for every time period are also dropped from consideration because they do not contribute to the conditional density of the log likelihood function (Chamberlain 1984).

Specific to the central analysis, household demand for leafy greens was estimated with the LP model with demographic variables and the RE probit model as follows:

$$\begin{aligned} y_{i,h,t} = \alpha + \boldsymbol{\beta}'\mathbf{RECALL}_{k,h,t} + \boldsymbol{\gamma}'\boldsymbol{p}_{k,h,t} + \boldsymbol{\delta}'\mathbf{INCOME}_h + \boldsymbol{\zeta}'\mathbf{HHSIZE}_h \\ + \boldsymbol{\theta}'\mathbf{CHILD}_h + \boldsymbol{\kappa}'\mathbf{MONTH}_t + \boldsymbol{\lambda}'\mathbf{YEAR}_t + \varepsilon_{i,b,h,t}. \end{aligned} \tag{15}$$

Additionally, demand was estimated using the LP model with household fixed effects and the FE logit model with the following specification:

$$y_{i,h,t} = \alpha + \boldsymbol{\beta}'\mathbf{RECALL}_{k,h,t} + \boldsymbol{\gamma}'\boldsymbol{p}_{k,h,t} + \boldsymbol{\kappa}'\mathbf{MONTH}_t + \boldsymbol{\lambda}'\mathbf{YEAR}_t + c_h + \varepsilon_{i,b,h,t}. \tag{16}$$

All four models were estimated four times. First, the models estimated the impact of all leafy green recall events on any leafy green purchase. Second, the models were estimated three more times to separately determine how purchases of romaine lettuce, iceberg lettuce, and spinach were impacted by romaine, iceberg and spinach recall events. In both equations (15) and (16), the dependent variable, $y_{i,h,t}$, is a binary variable indicating whether household h purchased leafy green i in month t. The independent variables representing prices, $\boldsymbol{p}_{k,h,t}$, are the average regional retail prices per ounce for all three leafy green types (romaine, iceberg, and spinach) faced by household h in month t. The own effect, the impact of $p_{i,h,t}$ on the likelihood of purchasing leafy green i, is expected to be negative. That is, as price decreases, it is expected that the probability of purchasing increases. The cross effect, the impact of $p_{j,h,t}$ on the likelihood of purchasing leafy green i, is less certain. If leafy greens i and j are substitutes, the cross effect is expected to be positive.

Household demographic characteristics, $\mathbf{INCOME}_h$, $\mathbf{HHSIZE}_h$, and $\mathbf{CHILD}_h$, that may impact the household likelihood of purchasing were also included as independent variables in the first specification, equation (15). Household income is reported by IRI as categorical variable. Thus, $\mathbf{INCOME}_h$ is a vector of dummy variables indicating the income range of household h from the last year the household participated in the panel. Similarly, $\mathbf{HHSIZE}_h$ is a vector of dummy variables indicating the size of household h

the last year the household participated in the panel. Household sizes range from one to eight individuals, and households with more than eight individuals are capped at eight. $\mathbf{CHILD}_h$ is a vector of dummy variables indicating households with young children (between the ages of 0 and 6), households with older children (between the ages of 6 and 13), and households with teenagers (between the ages of 13 and 18). Lastly, $\mathbf{MONTH}_t$ is a vector of variables indicating the month of the year and $\mathbf{YEAR}_t$ is a vector of variables indicating the year. These time fixed effects were included to account for any seasonal trends in the demand for leafy greens.

In both specifications, the proxies for food safety information and the variables of greatest interest are the dummy variables representing recalls of leafy greens, $\mathbf{RECALL}_{k,h,t}$, which is equal to one if a recall of leafy green k (either combined leafy greens, romaine, iceberg, or spinach) occurred during month t in the geographic region of household h, and is equal to zero otherwise. Note that the geographic region of a recall was defined as the region specified by FDA in the corresponding press release. As a result of heightened awareness following recall events and the severity of the health consequences, recalls of leafy greens as a result of pathogen contamination may act as a negative signal with which consumers update their risk perceptions. Consequently, as consumer perception of food safety declines, the likelihood of purchasing the potentially contaminated food product also declines. This Bayesian risk revision process is outlined in greater detail in Chapter III. Thus, for example, a spinach recall due to pathogen contamination is expected to decrease the likelihood of purchasing spinach. Conversely, if consumers consider lettuce (romaine or iceberg) to be a safe alternative to spinach as

Arnade, Calvin, and Kuchler (2009) suggest, the likelihood of purchasing lettuce is expected to increase.

Results

The results for the linear probability models, the random-effects probit model, and the conditional fixed-effects logit model for combined leafy green purchases are presented in Appendix C and the results distinguishing between romaine, iceberg, and spinach purchases are presented in Appendix D. Across estimations, the data reveal significant own-price effects confirming standard demand theory. Moreover, the own-price effects were greater in magnitude than any other factor, suggesting that price was the most dominant factor when deciding to purchase leafy greens. With regards to cross-price effects, the results suggest that romaine and iceberg were substitute goods. That is, as the price of iceberg increased, the likelihood of purchasing romaine increased, and vice versa. The relationship between spinach and other lettuces was less straightforward. As the price of spinach increased, the likelihood of purchasing romaine decreased. Yet as the price of romaine and iceberg increased, the likelihood of purchasing spinach also increased. However, insignificant or weak cross-price relationships, particularly between lettuce and spinach, were also documented by Arnade, Calvin, and Kuchler (2009).

The results from the LP ordinary least squares [OLS] and RE probit estimations reveal the impact of demographic factors on the likelihood of purchasing leafy greens. Households with incomes below the median were less likely to purchase romaine and spinach, and more likely to purchase iceberg. Above the median, households were more likely to purchase romaine and spinach, and less likely to purchase iceberg. The magnitude of these impacts increased the further removed from the median household.

These results are intuitive as iceberg lettuce was significantly less expensive when compared to romaine and spinach (see table 11). In terms of household size, larger households were more likely to purchase iceberg lettuce and less likely to purchase spinach, and the magnitude of the impact increased as household size increased. This relationship did not hold for romaine lettuce, but single-person households were less likely to purchase romaine lettuce as compared to other households. Lastly, households with children under the age of 13 were less like to likely to purchase iceberg and more likely to purchase spinach, perhaps because spinach is richer in nutrients than iceberg.

The parameters of greatest interest are the parameters corresponding to leafy green recall events. And to further interpret the results, the estimated coefficients were used to calculate average partial effects and odds ratios. The calculations for combined leafy green demand are presented in table 12. These results indicate that any leafy green recall event (whether romaine, iceberg, or spinach) had a negative but insignificant impact on the likelihood of purchasing a leafy green. Therefore, to determine whether households differentiated between risks linked to specific leafy greens, leafy green demand was further separated by variety.

Table 12. Estimated Average Partial Effects and Odds Ratios for Combined Leafy Green Recall Events

Average Partial Effects			
	LPM OLS	**LPM FE**	**RE Probit**
Leafy Green Recall	-0.0020** (0.0008)	-0.0013 (0.0007)	-0.0013 (0.0007)

Odds Ratios				
	LPM OLS	**LPM FE**	**RE Probit**	**FE Logit**
Leafy Green Recall	0.9903	0.9937	0.9937	0.9913

Note: Using the delta method, asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

The average partial effects and odds ratios for romaine, iceberg and spinach demand are presented in table 13. The own-recall effects (i.e., the impact of a romaine recall on the likelihood of purchasing romaine lettuce, etc.) were negative and significant when estimating the likelihood of purchasing romaine and iceberg, and negative but insignificant when estimating the demand for spinach. Furthermore, these results proved to be robust across empirical specifications. Thus, the results are consistent with expectations that recalls act as a negative signal with which consumers update their risk perceptions, thereby depressing the demand for the recalled product. In terms of cross-recall effects (i.e., the impact of a romaine recall on the likelihood of purchasing another leafy green, etc.), romaine recalls have a negative and significant impact on the likelihood of purchasing iceberg lettuce and a positive and significant impact on the likelihood of purchasing spinach. In other words, romaine recalls also depressed the demand for iceberg (another lettuce), but increased the demand for spinach indicating that consumers may consider spinach to be a safer alternative to lettuce. Conversely, focusing on the RE probit and FE logit results, spinach recalls had a positive and significant impact on the likelihood of purchasing romaine suggesting that during spinach recalls, consumers consider romaine to be a safer alternative to spinach. Iceberg recalls, however, had a negative impact on the likelihood of purchasing leafy greens across the board. That is, iceberg recalls also had a significant negative impact on the likelihood of purchasing spinach and an insignificant negative impact on the likelihood of purchasing romaine. However, it should be noted that the iceberg recall parameter may be the weakest recall parameter because only three iceberg recall events occurred between the years 2008 and 2012, as compared to romaine (18) and spinach (15).

Table 13. Estimated Average Partial Effects and Odds Ratios for Leafy Green Recall Events

Average Partial Effects

	Romaine Lettuce			Iceberg Lettuce		
	LPM OLS	**LPM FE**	**RE Probit**	**LPM OLS**	**LPM FE**	**RE Probit**
Romaine Recall	-0.0012* (0.0006)	-0.0016** (0.0006)	-0.0012* (0.0005)	-0.0042** (0.0006)	-0.0019** (0.0006)	-0.0025** (0.0006)
Iceberg Recall	-0.0018 (0.0013)	-0.0015 (0.0013)	-0.0019 (0.0013)	-0.0042** (0.0014)	-0.0082** (0.0013)	-0.0071** (0.0014)
Spinach Recall	0.0014 (0.0008)	0.0017* (0.0007)	0.0017** (0.0008)	-0.0035** (0.0008)	0.0001 (0.0007)	-0.0002 (0.0008)

Odds Ratios

	LPM OLS	**LPM FE**	**RE Probit**	**FE Logit**	**LPM OLS**	**LPM FE**	**RE Probit**	**FE Logit**
Romaine Recall	0.9883	0.9850	0.9878	0.9806	0.9648	0.9845	0.9791	0.9810
Iceberg Recall	0.9833	0.9857	0.9814	0.9771	0.9651	0.9322	0.9406	0.9224
Spinach Recall	1.0133	1.0159	1.0166	1.0231	0.9709	1.0006	0.9983	1.0026

Average Partial Effects

	Spinach		
	LPM OLS	**LPM FE**	**RE Probit**
Romaine Recall	0.0027** (0.0005)	0.0015** (0.0005)	0.0017** (0.0005)
Iceberg Recall	-0.0060** (0.0011)	-0.0045** (0.0011)	-0.0046** (0.0010)
Spinach Recall	-0.0008 (0.0007)	-0.0005 (0.0006)	-0.0005 (0.0006)

Odds Ratios

	LPM OLS	**LPM FE**	**RE Probit**	**FE Logit**
Romaine Recall	1.0380	1.0213	1.0243	1.0307
Iceberg Recall	0.9164	0.9378	0.9367	0.9164
Spinach Recall	0.9893	0.9932	0.9929	0.9906

Note: Using the delta method, asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

Ultimately, the results indicate that consumers do, in fact, react to food safety information, though the impact is small in magnitude relative to price and demographic factors. Also, the exact magnitude of impact varies by empirical specification; however, the differences between specifications are relatively minor, if not negligible. As mentioned earlier, one of the disadvantages of estimating an FE logit model (equation (14)) is the inability to estimate average partial effects. Thus, average partial effects were only estimated for the LP models and the RE probit model (table 13). Examining significant own-recall effects, the average impact across households of a romaine recall was a 0.12 to 0.16 percent reduction in the likelihood of purchasing romaine (depending on the specification). Similarly, the average impact of an iceberg recall was a 0.42 to 0.82 percent reduction in the likelihood of purchasing iceberg. The magnitude of these impacts may seem inconsequential at less than one percent, but bear in mind that the likelihood of a household purchasing lettuce (either romaine or iceberg) within a given month was already small to begin with at approximately 13 percent.

Though average partial effects cannot be estimated for the FE logit model, we can estimate odds ratios, defined as

$$\mathrm{OR} = \frac{\Pr(\mathrm{RECALL}=1)/(1-\Pr(\mathrm{RECALL}=1))}{\Pr(\mathrm{RECALL}=0)/(1-\Pr(\mathrm{RECALL}=0))} \tag{17}$$

where $\Pr(\mathrm{RECALL} = 1)$ is the probability of purchasing a leafy green (romaine lettuce, iceberg lettuce, or spinach) during the month of a recall event, $1 - \Pr(\mathrm{RECALL} = 1)$ is the probability of *not* purchasing a leafy green during the month of a recall event, and so on. To ensure that the results from all four empirical specifications are analogous, odds ratios for the LP models and RE probit model were also calculated using the coefficient results of Appendix D. Indeed, the estimated odds ratios are comparable across estimations; the range of odds ratios for a romaine recall on the likelihood of purchasing romaine lettuce was 0.9806 to 0.9883 and the range of odds ratios for an iceberg recall on the likelihood of purchasing iceberg lettuce was 0.9224 to 0.9651. Put another way, during the month of a romaine recall, the odds of purchasing romaine decreased by 1.17 to 1.94 percent and during the month of an iceberg recall, the odds of purchasing iceberg decreased by 3.49 to 7.76 percent.

Households with higher incomes and/or households with children may be more sensitive to external signals when making purchasing decisions. To test this possibility, the LP model with household fixed effects was estimated with the inclusion of interaction terms between the recall variables and demographic variables (equation (18)).[28]

$$\begin{aligned} y_{i,h,t} = \alpha &+ \boldsymbol{\beta}_1' \mathbf{RECALL}_{k,h,t} + \boldsymbol{\beta}_2' \mathbf{RECALL}_{k,h,t} \times \mathrm{INCOME}_h^{\mathrm{L}} \\ &+ \boldsymbol{\beta}_3' \mathbf{RECALL}_{k,h,t} \times \mathrm{INCOME}_h^{\mathrm{H}} + \boldsymbol{\beta}_4' \mathbf{RECALL}_{k,h,t} \times \mathrm{CHILD}_h^{12} \\ &+ \boldsymbol{\gamma}' \boldsymbol{p}_{k,h,t} + \boldsymbol{\kappa}' \mathbf{MONTH}_t + \boldsymbol{\lambda}' \mathbf{YEAR}_t + c_h + \varepsilon_{i,b,h,t}. \end{aligned} \tag{18}$$

Here, $\mathrm{INCOME}^{\mathrm{L}}$ is an indicator of whether the household reported an income less than 35,000, $\mathrm{INCOME}^{\mathrm{H}}$ is an indicator of whether the household reported an income of 70,000 or greater, and CHILD^{12} is a dummy variable indicating whether the household had children under 13. The results of these estimations, presented in table 14, reveal that there is no significant difference in response amongst households of different demographics, consistent with the results of Taylor, Klaiber, and Kuchler (2016). All households, regardless of children or income, were impacted by leafy green recalls to a certain extent.

[28] As a robustness check, the RE probit model with recall and demographic interaction terms was also estimated, but the results did not significantly differ for LP model with household fixed effects.

Table 14. Estimated Fixed Effects LPM Coefficients for Leafy Green Demand with Demographic Interaction Terms

	Romaine Lettuce	Iceberg Lettuce	Spinach
Romaine Recall	-0.0016 (0.0009)	-0.0019* (0.0009)	0.0021** (0.0008)
Iceberg Recall	-0.0011 (0.0021)	-0.0070** (0.0022)	-0.0031 (0.0018)
Spinach Recall	0.0014 (0.0012)	-0.0020 (0.0013)	-0.0005 (0.0010)
Household Income < $35,000			
Romaine Recall × INCOME^{L}	-0.0006 (0.0012)	0.0013 (0.0014)	-0.0018 (0.0011)
Iceberg Recall × INCOME^{L}	-0.0005 (0.0028)	0.0024 (0.0032)	0.0001 (0.0024)
Spinach Recall × INCOME^{L}	-0.0001 (0.0016)	-0.0043* (0.0019)	-0.0020 (0.0014)
Household Income ≥ $70,000			
Romaine Recall × INCOME^{H}	0.0004 (0.0013)	-0.0010 (0.0013)	-0.0010 (0.0011)
Iceberg Recall × INCOME^{H}	-0.0008 (0.0030)	-0.0049 (0.0029)	-0.0025 (0.0026)
Spinach Recall × INCOME^{H}	0.0005 (0.0017)	-0.0015 (0.0017)	-0.0015 (0.0014)
Households with Children Under the Age 13			
Romaine Recall × CHILD^{12}	0.0002 (0.0017)	0.0007 (0.0017)	0.0021 (0.0015)
Iceberg Recall × CHILD^{12}	0.0008 (0.0038)	-0.0008 (0.0039)	-0.0042 (0.0033)
Spinach Recall × CHILD^{12}	0.0005 (0.0023)	-0.0013 (0.0023)	0.0012 (0.0020)

Note: Coefficient results for the other variables are suppressed for the purposes of clarity and comparison. Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

Given that leafy green recalls significantly impact household purchases of leafy greens, albeit marginally, an informative sensitivity exercise is to determine the duration of the effect – the length of time that a consumer was influenced by a recall event when making purchase decisions. Under the Bayesian framework of Chapter III, we expect that without any additional signals after an initial shock, consumer perception of risk, and subsequently demand, eventually return to baseline levels. Therefore, equation (16) was re-estimated as an LP model with household fixed-effects with the inclusion of three lag variables: $\text{RECALL}_{h,t-1}$, $\text{RECALL}_{h,t-2}$, and $\text{RECALL}_{h,t-3}$. $\text{RECALL}_{h,t-1}$ is equal to one if a recall occurred within the previous month (month $t-1$) and is equal to zero otherwise,$\text{RECALL}_{h,t-2}$ is equal to one if a recall occurred at least two months ago (month $t-2$) and equal to zero otherwise, and so on. The results of these estimations, presented in table 15, reveal that households, for the most part, were influenced by leafy green recall events within the first month following the recall before reverting back to previous consumption behavior. Such short-term behavior modification with respect to food safety information is consistent with the findings of several previous empirical analyses (e.g., Dahlgran and Fairchild 2002; Piggott and Marsh 2004). However, these results differ from the results of Arnade, Kuchler, and Calvin (2011). They concluded that the spinach contamination event of 2006 impacted consumer purchases of bagged spinach for 8.5 weeks. However, Arnade, Kuchler, and Calvin analyzed the impact of a single, major event, whereas the present analysis considers the impact of multiple smaller, delineated events, which may account for the difference in results.

The one exception in terms of duration of impact was the impact of iceberg recalls on the likelihood of purchasing iceberg lettuce, which was positive and significant in the second and third month following the initial recall month. One explanation for this positive lag impact may be some sort of rebound effect; after forgoing to purchase iceberg lettuce for a period of time, households may have been anxious to purchase again after they deemed a sufficient amount of time had elapsed since the initial negative signal. Another possibility may be that recalls serve as a short-run negative signal for food safety; but in the long-run, also serve as a positive signal for food supply oversight. That is, in the long-run, recalls may signal that federal authorities are adequately monitoring the nation's food supply by removing contaminated food products from the marketplace. Thus, following an initial shock, overall faith in the system is improved, resulting in a positive lag impact.[29]

Table 15. Estimated Fixed Effects LPM Coefficients for Leafy Green Demand with Lag Terms

Duration of the Recall Effect	
Romaine Lettuce	
Month 1 ($\mathrm{RECALL}_{h,t}$)	-0.0016** (0.0005)
Month 2 ($\mathrm{RECALL}_{h,t-1}$)	0.0005 (0.0005)
Month 3 ($\mathrm{RECALL}_{h,t-2}$)	-0.0009 (0.0005)
Month 4 ($\mathrm{RECALL}_{h,t-3}$)	0.0004 (0.0006)
Iceberg Lettuce	
Month 1 ($\mathrm{RECALL}_{h,t}$)	-0.0083** (0.0013)
Month 2 ($\mathrm{RECALL}_{h,t-1}$)	0.0020 (0.0013)
Month 3 ($\mathrm{RECALL}_{h,t-2}$)	0.0081** (0.0013)
Month 4 ($\mathrm{RECALL}_{h,t-3}$)	0.0036** (0.0013)
Spinach	
Month 1 ($\mathrm{RECALL}_{h,t}$)	-0.0003 (0.0006)
Month 2 ($\mathrm{RECALL}_{h,t-1}$)	0.0002 (0.0006)
Month 3 ($\mathrm{RECALL}_{h,t-2}$)	0.0002 (0.0006)
Month 4 ($\mathrm{RECALL}_{h,t-3}$)	-0.0001 (0.0006)

Note: Coefficient results for the other variables are suppressed for purposes of clarity and comparison. Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

[29] However, as mentioned earlier, the iceberg recall parameters may be the weakest recall parameters because only three iceberg recall events occurred between the years 2008 and 2012.

Lastly, to further interpret the results, predicted probabilities from the LP model with household fixed effects were used to approximate the fiscal impacts of nationwide romaine and iceberg recalls. When households purchased leafy greens in the IRI Consumer Network, they purchased a monthly median amount of 18 ounces of romaine lettuce and 16 ounces of iceberg lettuce at an average of 0.219 dollars per ounce and 0.145 dollars per ounce, respectively. Using these figures, national household population estimates for 2008 to 2012, [30] and the predicted probabilities that a household purchased romaine or iceberg lettuce during a month with and without a recall, the estimate of romaine lettuce revenue loss from a nationwide romaine recall was approximately 635,000 dollars or 1.3 percent of monthly industry revenues. The loss of iceberg lettuce revenues from an iceberg lettuce recall was even greater at approximately 1.94 million dollars or 5.9 percent of monthly industry revenues. However, these estimates only consider significant own-recall effects and ignore significant negative and positive cross-recall effects. Moreover, the estimates of revenue loss only account for packaged leafy green products, and do not include bulk, random-weight leafy greens and leafy greens sold through other marketing channels (foodservice, institutional, etc.).

Conclusion

The objective of this analysis was to investigate the impact of food safety information on the demand for leafy greens. Analyzing disaggregated household purchase data and FDA leafy green recall data, the results reveal that recall events had a statistically significant

[30] The source for household population was the U.S. Census Bureau, 2008-2012 American Community Survey 5-Year Estimates. Additionally, we assumed only 89 percent of households consumed leafy greens given that only 89 percent of households participating in the IRI Consumer Network purchased leafy greens.

impact on leafy green consumption, though the impact was small relative to price and demographic factors and often disappeared after a month's time. Specifically, the own-recall effects were negative and significant when estimating the likelihood of purchasing romaine and iceberg lettuce; the cross-recall effects were negative and significant when estimating the impact of romaine recalls on the likelihood of purchasing iceberg lettuce and when estimating the impact of iceberg recalls on the likelihood of purchasing spinach; and lastly, the cross-recall effects were positive and significant when estimating the impact of romaine recalls on the likelihood of purchasing spinach and vice versa.

The final results are mainly consistent with much of the existing empirical literature, in that the results provide further evidence that food safety information has negative effects on the demand for the contaminated product involved (Smith, van Ravenswaay, and Thompson 1988; Foster and Just 1989; Burton and Young 1996; Dahlgran and Fairchild 2002; Marsh, Schroeder, and Mintert 2004; Piggott and Marsh 2004; Shimshack, Ward, and Beatty 2007; Arnade, Calvin, and Kuchler 2009; Tonsor, Mintert, and Schroeder 2010; Arnade, Kuchler, and Calvin 2011), significant cross effects on the demand for other products (Burton and Young 1996; Marsh, Schroeder, and Mintert 2004; Piggott and Marsh 2004; Arnade, Calvin, and Kuchler 2009; Tonsor, Mintert, and Schroeder 2010), and eventually return to initial demand levels (Dahlgran and Fairchild 2002; Piggott and Marsh 2004). However, the present results differ in several critical ways. First, using household locational data, the present study addresses the regional nature of most recall events by identifying and analyzing the purchases of households experiencing a recall in their geographic region in any given monthly period. Second, in direct contrast with studies that have aggregated data across quarters or greater time periods, the chosen monthly periodicity allows for the analysis of immediate short-run impacts. This distinction is of particular importance given that, the results reveal that the impact of recall events of leafy green consumption generally did not last for more than one month. Third, and lastly, as opposed to studies analyzing aggregate consumption data, the present study considers possible heterogeneity of household responses and interaction terms of recalls with household income and composition. Ultimately, the results reveal that all households were significantly affected by recall events, independent of household income and composition.

The dramatic increase in the number of incidents of foodborne illness linked to leafy greens and the number of leafy green products recalled over the past decade highlights the need for a complete understanding of consumer behavior in response to leafy green recalls. The present results indicate that despite the removal of contaminated leafy green products from retail locations, some consumers responded to recall events by deciding not to purchase the implicated green in the weeks immediately following. This observation suggests that at least some consumers use recall events to gauge product quality and safety, and that they believe recall events signal lower quality, riskier products. In turn, this translates to lost sales for all leafy green producers, not just the firm liable for the contaminated product. Thus, greater consumer education and awareness with regards to the safety and quality of the products that remain on the market following a recall may lessen the magnitude of the impact and benefit the industry as a whole. Additionally, a reduction in recalls through increased protection against bacterial contamination may have the potential to further benefit both consumers and producers.

V. Demand Impacts of Ground Beef Product Recalls

Escherichia coli (*E. coli*) are a large and diverse group of bacteria found in the environment, foods, and intestines of humans and animals. Most *E. coli* bacteria are harmless; however a small group of *E. coli* produce a Shiga toxin (Shiga toxin-producing *E. coli* or STEC) that may cause severe damage to the lining of the intestine. The actual infectious dose is unknown, but most scientists believe it takes only a small amount to cause serious illness and even death, especially in children and older adults (FSIS 2016). Illnesses caused to STEC, most notably *E. coli* O157:H7, are frequently linked to the consumption of undercooked ground beef. Between 1982 and 2002, ground beef was the most common vehicle for *E. coli* O157:H7 foodborne illness outbreaks (Rangel et al. 2005). More recently, between 1998 and 2008, beef was again the most common vehicle for STEC foodborne illness outbreaks (Gould 2013). Naturally, ground beef poses a greater health risk than other cuts of beef because of the risk of possible cross-contamination from grinding.

Concerns of bacterial contamination and foodborne illness have the strong potential to influence the demand for ground beef. As theorized in Chapter III and demonstrated in Chapter IV with leafy green recalls, recalls signal negative information to consumers about relative health risks. Recently, Taylor, Klaiber, and Kuchler (2016) confirmed this relationship with ground beef. They estimated the impact of ground beef recalls on consumer demand for ground beef between January 2002 and December 2005 and found clear, significant evidence of a structural change in these impacts following the discovery of a BSE-positive cow in the United States in December 2003. That is, they found ground beef recalls had no impact on household purchases of ground beef prior to the discover of

BSE in the United States, but following the 2003 BSE discovery event, consumers responded to ground beef recall events by purchasing significantly less ground beef.

The primary objective of this chapter is to investigate the effect of STEC-contaminated ground beef recalls on the demand for ground beef products with updated data. Using disaggregated household demographic and purchasing data, this study effectively takes advantage of the temporal and geographic variability of STEC contaminated ground beef recalls in order to accurately measure the impact of food safety information on the demand for ground beef products. Most importantly, however, the present analysis also considers the strength of the signal. That is, in contrast to Taylor, Klaiber, and Kuchler (2016) and the leafy green analysis of the previous chapter, the present analysis differentiates between recalls prompted by consumer illness investigations and recalls prompted by pathogen testing. Assuming consumers perceive recalls prompted consumer illnesses to be stronger health risk signals than recalls prompted by laboratory testing, then, as demonstrated by the Bayesian theoretical framework of Chapter III, the impact of recalls prompted by consumer illnesses is expected to be greater than the impact of recalls prompted by pathogen testing. Additionally, the length of time to recovery, the time needed to return to baseline purchasing behavior, is also expected to be greater following recalls prompted by consumer illnesses.

Ground Beef Recall Data

Information about ground beef recall events was gathered from FSIS press releases, discussed in greater detail in Chapter I. Every recall under FSIS authority is the subject of a press release with very few exceptions. Between 2008 and 2012, FSIS oversaw 377 recall events; 106 (28 percent) of which were beef or veal products. Of these 106 beef and veal recalls, 58 (55 percent) were ground beef products recalled due to STEC contamination. STEC contamination accounted for 75 percent of all ground beef recall events, and details of these 58 recall events are summarized in table 16. Relevant to the present analysis, note that 17 of the 58 recall events (29 percent) were the result of a consumer illness investigation and the remaining 41 recall events were the result of pathogen discovery through laboratory testing. Thus, ground beef recalls provide an excellent case study to analyze the impact of signal strength because there exists sufficient variability in the number of recalls prompted by consumer illness outbreaks and the number of recalls prompted by pathogen testing.

Table 16. Summary Statistics of STEC Ground Beef Recall Events, 2008-2012

	2008[a]	**2009**	**2010**	**2011**	**2012**	**Total**[a]
Total STEC Ground Beef Recall Events	15	16	10	12	5	58
Nationwide Events	3	3	0	0	0	6
Events Linked to a Consumer Illness	6	5	3	2	1	17
Mean Recall Quantity (lbs.)	548,278	85,506	705,065	81,694	12,693	296,253
Standard Error (lbs.)	409,002	42,360	570,345	33,220	6,936	139,702
Maximum Recall Quantity (lbs.)	5,300,000	545,699	5,764,000	377,775	38,200	5,764,000
Minimum Recall Quantity (lbs.)	345	68	2,574	500	2,057	68
Total No. of Pounds Recalled (lbs.)	7,127,608	1,368,100	7,050,647	980,331	63,467	16,590,153
Total No. of Pounds Recovered (lbs.)	2,701,999	540,757	398,826	432,038[b]	339,062	4,412,682[b]

[a] Recall quantity data were not available for two recalls in 2008.
[b] Pounds recovered data were not available for one recall in 2011.

As in the previous chapter, the greatest advantage of using multiple recall events to measure the impact of food safety information is the temporal and geographic variability. Of the 58 ground beef recall events due to STEC contamination, only six included ground beef products that were distributed nationwide. The remaining recalled products were distributed to regions identified by the firm and FSIS in the press release, and the size of the affected regions ranged from a single city or county to several states. For example, the average regional recall impacted three states, while the most expansive regional recall impacted 34 states.

Household Demographic and Purchasing Data

Once more, the primary dataset used in this analysis is the IRI Consumer Network™. The years of interest were 2008 to 2012 and the product of interest was fresh or frozen packaged, uniform-weight ground beef. The data on ground beef purchases include a detailed product description, date of purchase, total quantity, and total expenditure for every item. The data of household demographics include county of residence, household composition, household size, income, education, age, and race. As explained in greater detail in Chapter IV, the demographics data contain only a snapshot of household characteristics from 2012 or the last year each household reported demographic data.

A drawback of the IRI Consumer Network is that static households only record and report their purchases of uniform-weight, UPC-coded products. For commodities like ground beef, which is often sold as a store-packed, random-weight product, this may create a problem as the data ignore a significant share of the market. Though it is not possible to consider the impact of ground beef recalls on random-weight purchases from 2008 to 2012, it is possible to compare trends in household expenditures on random-weight and uniform-weight ground beef purchases for 2012 and 2013. For the subset of households participating in the random-weight consumer panel in 2012 and 2013, figure 13 plots total monthly expenditures on random-weight and uniform-weight ground beef.

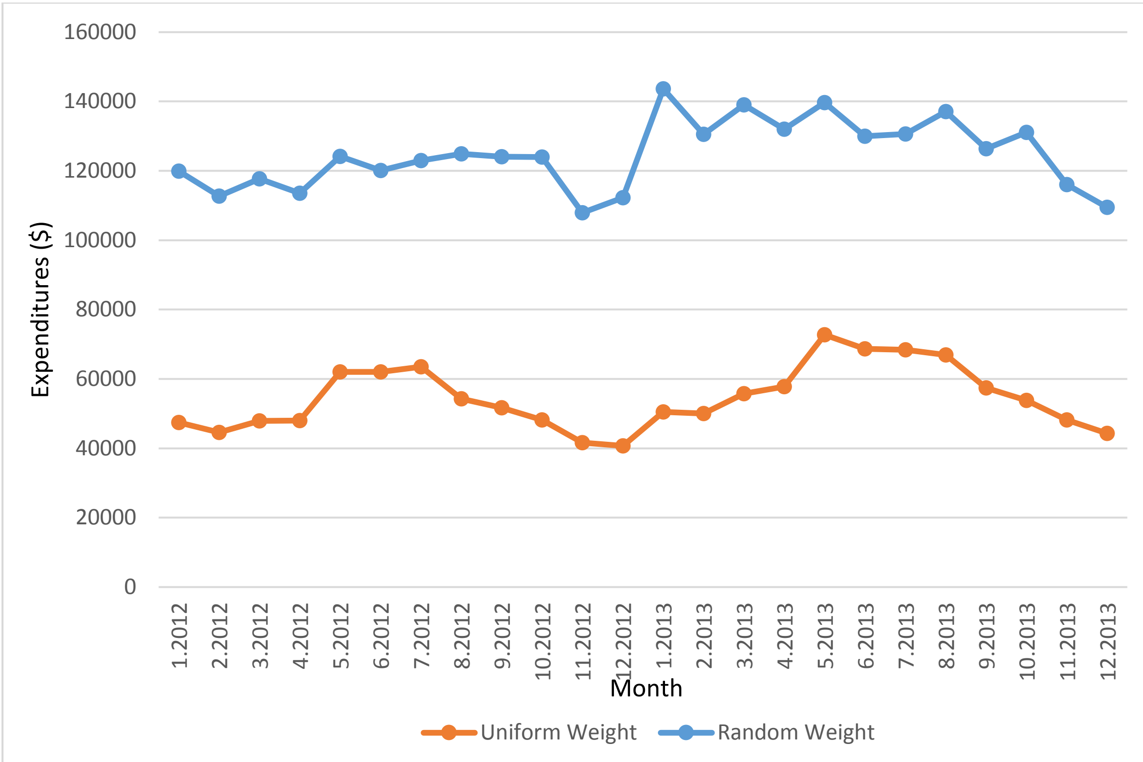

Figure 13. Total Monthly Expenditures on Random Weight and Uniform Weight Ground Beef Products, 2012-2013.
Data: Random Weight Static Households, IRI Consumer Network.[31]

Expenditures on random-weight ground beef were roughly twice as much as expenditures on uniform-weight ground beef; however, the purchasing patterns between random-weight and uniform-weight ground beef appear to be strongly correlated. In fact, the Pearson correlation coefficient between random-weight expenditures and uniform-weight expenditures is 0.65. This positive correlation suggests that the demand impacts of STEC-contaminated ground beef recall events on uniform-weight ground beef purchases are likely analogous to the impacts on random-weight ground beef purchases.

[31] In 2012, 33,854 households participated in the random-weight consumer panel. In 2013, 36,529 households participated.

Several additional specifications were made to further aid analysis. First, a monthly periodicity was chosen to avoid high censoring rates, while still remaining precise enough to examine short-run food safety effects. Of the households that purchased ground beef products within a surveyed year, the average number of packaged ground beef products purchased was four. And of households that purchased a ground beef product within a surveyed month, 74 percent purchased only one packaged ground beef product. Given that the majority of households that purchased a ground beef product within a given month only purchased ground beef once, a monthly periodicity is justifiable. Additionally, if a household recorded no purchases in a given month, ground beef or otherwise, the month was omitted from analysis.

Second, only households that purchased packaged ground beef products at least once during the surveyed period were considered for analysis. By only analyzing the consumption behavior of these households, we focus our attention on the households that were most likely to be impacted by ground beef recall events. Thus, the final dataset was reduced from 106,718 static households to 67,446 households. Summary statistics of selected characteristics of participating households as compared to the full IRI panel and Census figures are presented in table 17. The households selected for analysis had an average number of persons per household of 2.60,[32] almost exactly the same as the national average household size estimated by the Census Bureau, 2.61. Households also had a median annual income range of 50,000 to 59,999 dollars, consistent with the

[32] Mean household size may be biased downwards because the number of reported individuals per household is capped at eight. However, households of eight or more members only account for 0.48 percent of households in the final panel.

Census Bureau statistic of $53,046.[33] And lastly, 26.5 percent of selected households included an individual under the age of 18.

Table 17. Selected Demographic Distributions from the IRI Consumer Network (%)

	Census[a]	Full IRI Static Panel	Final Panel Dataset
Household Size			
1	27.5	23.0	18.7
2	33.5	41.2	41.8
3	15.9	14.5	15.6
4		12.7	14.0
5		5.4	6.1
6	23.2	2.1	2.5
7		0.7	0.8
8+		0.4	0.5
Household Income			
$0-$14,999	12.6	6.9	6.6
$15,000-$24,999	10.7	9.7	9.6
$25,000-$34,999	10.4	12.6	12.7
$35,000-$49,999	13.7	17.6	17.9
$50,000-$59,999		10.3	10.5
$60,000-$69,999	30.4	8.1	8.3
$70,000-$99,999		19.7	19.9
$100,000+	22.2	15.2	14.5
Presence of Children			
Children under 18	32.8	24.2	26.5
No children under 18	67.2	75.8	73.5
No. of Households	115,226,802	106,718	67,446

[a] Source: U.S. Census Bureau, 2008-2012 American Community Survey 5-Year Estimates

Third, and lastly, price per ounce of ground beef was calculated by dividing total monthly expenditures (dollars) by total monthly quantity purchased (ounces). However, as in the previous chapter, the analysis could not depend on observed prices alone. Therefore, once again, the average regional price from store-sales data was calculated for

[33] Household income is reported by IRI as a categorical variable, not a continuous variable.

each of the 73 IRI-defined markets. Table 18 summarizes and compares average retail regional prices with observed prices.

Table 18. Summary Statistics of Observed and Average Regional Prices for Ground Beef

	No. of Observations	Mean Price ($/oz.)	Standard Deviation
Observed	446,914	0.187	0.068
Regional Average	2,446,036[a]	0.195	0.030

[a] The total number of household month observations is 2,446,480. The average regional retail prices for packaged ground beef are not complete because the price for ground beef was not available for the Boise, ID market in July 2008, September 2008, October 2008, and December 2011 and not available for the Syracuse, NY market in November 2008. As no ground beef products were recalled in these regions during the specified months, these missing price observations should not significantly impact results.

Empirical Estimation

The disaggregated household IRI panel and the FSIS recall data allow for a unique empirical analysis of the impact of food safety information on household ground beef purchases. As in Chapter IV, demand was estimated using a binary response model, the general formulation of which is expressed by equation (11). That is, the focus of this analysis was on the household decision to purchase rather than the quantitative decision of how much to purchase (given that the household had already decided to buy).

Following the outline of the previous chapter, four methods were employed to estimate the binary response model: a linear probability [LP] model with time-invariant demographic variables; an LP model with household fixed effects (equation (12)); a random-effects [RE] probit model (equation (13)), and a conditional fixed-effects [FE] logit model (equation (14)). Household demand for ground beef was estimated with the LP model with demographic variables and the RE probit model using the following specification:

$$y_{h,t} = \alpha + \beta_1 \text{RECALL}_{h,t}^{CI} + \beta_2 \text{RECALL}_{h,t}^{PT} + \gamma p_{h,t} + \boldsymbol{\delta}'\mathbf{INCOME}_h$$
$$+\boldsymbol{\zeta}'\mathbf{HHSIZE}_h \; + \; \boldsymbol{\theta}'\mathbf{CHILD}_h + \boldsymbol{\kappa}'\mathbf{MONTH}_t + \boldsymbol{\lambda}'\mathbf{YEAR}_t + \varepsilon_{i,b,h,t}. \qquad (19)$$

And demand was estimated using the LP model with household fixed effects and the FE logit model with the following specification:

$$y_{h,t} = \alpha + \beta_1 \text{RECALL}_{h,t}^{CI} + \beta_2 \text{RECALL}_{h,t}^{PT} + \gamma p_{h,t} + \boldsymbol{\kappa}'\mathbf{MONTH}_t + \boldsymbol{\lambda}'\mathbf{YEAR}_t$$
$$+c_h + \varepsilon_{i,b,h,t}. \qquad (20)$$

In both equations (19) and (20), the dependent variable, $y_{h,t}$, is a binary variable indicating whether household h purchased packaged ground beef in month t. The independent variable representing price, $p_{h,t}$, is the average regional retail price per ounce of packaged ground beef faced by household h in month t. The impact of $p_{h,t}$ on the likelihood of purchasing ground beef is, of course, expected to be negative. In equation (19), independent variables representing household demographic characteristics, $\mathbf{INCOME}_h$, $\mathbf{HHSIZE}_h$, and $\mathbf{CHILD}_h$, were also included as they may also impact the likelihood a household purchased ground beef.[34] $\mathbf{INCOME}_h$ is a vector of dummy variables indicating the income range of household h from the last year the household participated in the panel. $\mathbf{HHSIZE}_h$ is a vector of dummy variables indicating the size of household h the last year the household participated in the panel. And $\mathbf{CHILD}_h$ is a vector of dummy variables indicating households with young children (between the ages of 0 and 6), households with older children (between the ages of 6 and 13), and households with teenagers (between the ages of 13 and 18). Lastly, time fixed effects were included in both specifications to account for any seasonal trends in the demand for

[34] However, the time-invariant demographic variables are eliminated from the LP model with household fixed effects and the FE logit model due to collinearity.

ground beef. $\mathbf{MONTH}_t$ is a vector of variables indicating the month of the year and $\mathbf{YEAR}_t$ is a vector of variables indicating the year.

For both specifications, the proxies for food safety information and the variables of greatest interest, are the dummy variables representing recalls of ground beef, $\text{RECALL}_{h,t}^{CI}$ and $\text{RECALL}_{h,t}^{PT}$. $\text{RECALL}_{h,t}^{CI}$ is equal to one if a STEC-contaminated ground beef recall following a consumer illness investigation occurred during month t in the geographic region of household h, and is equal to zero otherwise. Similarly, $\text{RECALL}_{h,t}^{PT}$ is equal to one if a STEC-contaminated ground beef recall following pathogen testing occurred during month t in the geographic region of household h, and is equal to zero otherwise. Note that the geographic region of a recall was defined as the region specified by FSIS in the corresponding press release. As a result of heightened awareness following recall events and the severity of the health consequences, recalls of STEC-contaminated ground beef may act as a negative signal with which consumers update their risk perceptions. Consequently, as consumer perception of food safety declines, the likelihood of purchasing the potentially contaminated food product also declines. Furthermore, stronger signals, such as recalls prompted by illness outbreaks ($\text{RECALL}_{h,t}^{CI}$) likely have a greater impact on the likelihood of purchasing ground beef than weaker signals, such as recalls prompted by laboratory testing ($\text{RECALL}_{h,t}^{PT}$). Motivations and predictions for the empirical specification are outlined in greater detail by the Bayesian theoretical framework of a utility maximizing consumer facing risk uncertainty in Chapter III.

Results

The results from the linear probability models, the random-effects probit model, and the conditional fixed-effects logit model are presented in Appendix E. Across estimations, the data reveal significant price effects validating *a priori* expectations. Moreover, the price effects were greater in magnitude than any other factor, suggesting that price was the most dominant factor when deciding to purchase packaged ground beef.

The results from the LP ordinary least squares [OLS] and RE probit estimations reveal the impact of demographic factors. Households with incomes below the median were more likely to purchase packaged ground beef, and households with incomes above the median were less likely to purchase ground beef, with demand declining as household income increased. These results suggest that as income increases, households abandon packaged meat purchases and perhaps opt for other products, such as finer cuts of meat or deli-counter (butchered) ground beef that are sold without UPC codes. In terms of household size, larger households were more likely to purchase packaged ground beef and the magnitude of the impact increased as household size increased. Lastly, households with young children (under the age of six) were less likely to purchase packaged ground beef, and according to the RE probit results, households with teenagers (individuals between the age of 13 and 18) were more likely to purchase packaged ground beef.

Of course, the variables of greatest interest are those corresponding to ground beef recall events. To further make sense of the results and to compare values across models, the estimated coefficients were used to calculate average partial effects and odds ratios. These calculations are presented in table 19. Across estimations, the recall parameters, both for recalls prompted by consumer illness investigations and those prompted by pathogen testing, were negative and significant at the five or one percent level when estimating the likelihood of purchasing packaged ground beef. Thus, the results are consistent with expectations that recalls act as a negative signal with which consumers update their perceptions of risk, thereby depressing the demand for the recalled product. Examining differences in pathogen discovery, the results from the LPM FE, RE probit, and FE logit estimations indicate that consumer illness recalls had a greater impact than pathogen testing recalls. This suggests that recalls prompted by confirmed illnesses are stronger signals than recalls prompted by pathogen testing because consumers were more responsive to the former, though tests of equality could not be rejected at the five percent level.[35]

Table 19. Estimated Average Partial Effects and Odds Ratios for Ground Beef Recall Events

Average Partial Effects	**LPM OLS**	**LPM FE**	**RE Probit**
Consumer Illness Recall	-0.0051** (0.0008)	-0.0036** (0.0008)	-0.0047** (0.0008)
Pathogen Testing Recall	-0.0104** (0.0011)	-0.0021* (0.0013)	-0.0038** (0.0011)

Odds Ratios	**LPM OLS**	**LPM FE**	**RE Probit**	**FE Logit**
Consumer Illness Recall	0.9664	0.9762	0.9703	0.9658
Pathogen Testing Recall	0.9315	0.9860	0.9763	0.9801

Note: Using the delta method, asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

[35] The p-values to test the equality of the consumer illness recall coefficient and the pathogen testing recall coefficient were 0.2169 for the LP model with household fixed effects, 0.4636 for the RE probit model, and 0.1574 for the FE logit model.

The results indicate that consumers may, indeed, consider signal content and interpret signals with varying levels of information differently. The exact magnitude of impact varies by empirical specification. As described in Chapter IV, one of the disadvantages of estimating an FE logit model (equation (16)) is the inability to estimate average partial effects. Thus, average partial effects were only estimated for the LP models and the RE probit model. Examining the significant effects from the FE LP and RE probit models,[36] the average impact across households of a STEC ground beef recall due to pathogen testing was a 0.21 to 0.38 percent reduction in the likelihood of purchasing packaged ground beef products (with significance at the five percent level). The average impact of a recall due to a consumer illness investigation was greater at a 0.36 to 0.47 percent reduction in the likelihood of purchasing packaged ground beef products (with significance at the one percent level). The magnitude of these impacts may seem insignificant at less than one percent, but note that the likelihood of a household purchasing packaged ground beef within a given month was already small to begin with at approximately 18 percent.

Though average partial effects cannot be estimated for the FE logit model, it is possible to estimate odds ratios (equation 19). So, to compare the results across all four empirical specifications, odds ratios for the LP models and RE probit models were also calculated using the coefficient results of Appendix E. Depending on the specification, the range of odds ratios for a pathogen testing recall on the likelihood of purchasing packaged ground beef was 0.9763 to 0.9860 and the range of odds ratios for a consumer

[36] The average partial effects from the LPM OLS estimation are not included in the discussion given the relatively low R-squared value, which is problematic for precise predictions. Moreover, the results from the LPM OLS model differ considerably from the other three other models.

illness recall was 0.9658 to 0.9762. Put another way, during the month of pathogen testing recall, the odds of purchasing packaged ground beef decreased by 1.40 to 2.37 percent, and during the month of a consumer illness recall, the odds decreased by 2.38 to 3.42 percent.

The extent to which households respond to recall events may vary by demographic factors, such as income and the presence of children. To test this possibility, the LP model with household fixed effects was estimated with the inclusion of interaction terms between the recall variables and demographic variables (equation (21)).

$$\begin{aligned} y_{h,t} = \alpha &+ \beta_1 \mathrm{RECALL}_{h,t}^{CI} + \beta_2 \mathrm{RECALL}_{h,t}^{PT} \\ &+\beta_3\left(\mathrm{RECALL}_{h,t}^{CI} \times \mathrm{INCOME}_h^{\mathrm{L}}\right) + \beta_4\left(\mathrm{RECALL}_{h,t}^{PT} \times \mathrm{INCOME}_h^{\mathrm{L}}\right) \\ &+\beta_5\left(\mathrm{RECALL}_{h,t}^{CI} \times \mathrm{INCOME}_h^{\mathrm{H}}\right) + \beta_6\left(\mathrm{RECALL}_{h,t}^{PT} \times \mathrm{INCOME}_h^{\mathrm{H}}\right) \\ &+\beta_7\left(\mathrm{RECALL}_{h,t}^{CI} \times \mathrm{CHILD}_h^{12}\right) + \beta_8\left(\mathrm{RECALL}_{h,t}^{PT} \times \mathrm{CHILD}_h^{12}\right) \\ &+\gamma p_{h,t} + \boldsymbol{\kappa}'\mathbf{MONTH}_t + \boldsymbol{\lambda}'\mathbf{YEAR}_t + c_h + \varepsilon_{i,b,h,t}. \end{aligned} \tag{21}$$

Here, $\mathrm{INCOME}^{\mathrm{L}}$, an indicator of whether the household reported an income less than 35,000; $\mathrm{INCOME}^{\mathrm{H}}$, an indicator of whether the household reported an income of 70,000 or greater; and CHILD^{12}, a dummy variable indicating whether the household had children under 13. The results of these estimations, presented in table 20, reveal that there is no significant difference in response amongst households of different demographics (at the one percent level), consistent with the results of Chapter IV and Taylor, Klaiber, and Kuchler (2016). All households, regardless of children or income, were impacted by ground beef recalls to a certain extent, particularly recalls resulting from consumer illness investigations.

Table 20. Estimated Fixed Effects LPM Coefficients for Ground Beef Demand with Demographic Interaction Terms

	Estimated Coefficients
Consumer Illness Recall	-0.0033** (0.0013)
Pathogen Testing Recall	-0.0008 (0.0016)
Household Income < $35,000	
Consumer Illness Recall × INCOME^{L}	-0.0043* (0.0018)
Pathogen Testing Recall × INCOME^{L}	-0.0016 (0.0023)
Household Income ≥ $70,000	
Consumer Illness Recall × INCOME^{H}	-0.0032 (0.0021)
Pathogen Testing Recall × INCOME^{H}	0.0008 (0.0018)
Households with Children Under the Age 13	
Consumer Illness Recall × CHILD^{12}	0.0055* (0.0025)
Pathogen Testing Recall × CHILD^{12}	0.0022 (0.0030)

Note: Coefficient results for the other variables are suppressed for purposes of clarity and comparison. Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

Lastly, under the Bayesian framework of Chapter III, we expect that after the initial impact of a recall, consumer perception of risk, and subsequently demand, eventually return to baseline levels. The length of time to recovery is a function of the strength of the signal and the weight consumers place on their own experiences versus negative information signals, and we expect stronger signals to require greater recovery times. To test this hypothesis, equation (20) was re-estimated as an LP model with household fixed-effects and the inclusion of six lag variables: $\text{RECALL}_{h,t-1}^{\text{CI}}$, $\text{RECALL}_{h,t-2}^{\text{CI}}$, $\text{RECALL}_{h,t-3}^{\text{CI}}$, $\text{RECALL}_{h,t-4}^{\text{CI}}$,$\text{RECALL}_{h,t-1}^{\text{PT}}$, and $\text{RECALL}_{h,t-2}^{\text{PT}}$.[37]

[37] Four lag variables for consumer illness recalls and two lag variables for pathogen testing recalls were included based on the decrease in magnitude and significance.

$\mathrm{RECALL}_{h,t-1}^{\mathrm{CI}}$ is equal to one if a consumer illness recall occurred within the previous month (month $t-1$) and is equal to zero otherwise, $\mathrm{RECALL}_{h,t-2}^{\mathrm{CI}}$ is equal to one if a recall occurred at least two months ago (month $t-2$) and equal to zero otherwise, and so on.

The results of these estimations, presented in table 21, reveal that households were influenced by ground beef recall events prompted by pathogen testing for the first month following the recall event before reverting back to previous consumption behavior, though this result is statistically different from zero only at the five percent level. In contrast, households were influenced by ground beef recall events prompted by consumer illness investigations for nearly three months following the recall event. While the estimated coefficient for the first lag variable is not significantly different from zero, the coefficient for the second lag variable is statistically different from zero and smaller in magnitude than the coefficient for the initial recall month. The coefficients for the third and fourth lag variables are smaller still and statistically insignificant, suggesting the impact of the consumer illness recalls may not persist beyond three months.

Table 21. Estimated Fixed Effects LPM Coefficients for Ground Beef Demand with Lag Terms

Duration of the Recall Effect	
Consumer Illness Recall	
Month 1 ($\mathrm{RECALL}_{h,t}^{\mathrm{CI}}$)	-0.0040** (0.0009)
Month 2 ($\mathrm{RECALL}_{h,t-1}^{\mathrm{CI}}$)	-0.0006 (0.0008)
Month 3 ($\mathrm{RECALL}_{h,t-2}^{\mathrm{CI}}$)	-0.0023** (0.0008)
Month 4 ($\mathrm{RECALL}_{h,t-3}^{\mathrm{CI}}$)	0.0004 (0.0008)
Month 5 ($\mathrm{RECALL}_{h,t-4}^{\mathrm{CI}}$)	-0.0004 (0.0008)
Pathogen Testing Recall	
Month 1 ($\mathrm{RECALL}_{h,t}^{\mathrm{PT}}$)	-0.0022* (0.0010)
Month 2 ($\mathrm{RECALL}_{h,t-1}^{\mathrm{PT}}$)	0.0011 (0.0010)
Month 3 ($\mathrm{RECALL}_{h,t-2}^{\mathrm{PT}}$)	0.0000 (0.0010)

Note: Coefficient results for other variables are suppressed for purposes of clarity and comparison. Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

To further interpret the results, predicted probabilities from the LP model with household fixed effects were used to approximate the fiscal impacts of nationwide ground beef recalls. When households purchased packaged ground beef in the IRI Consumer Network, they purchased a monthly median amount of 48 ounces at an average of 0.195 dollars per ounce. Using these figures, national household population estimates for 2008 to 2012,[38] and the predicted probabilities that a household purchased packaged ground beef during a month with and with a recall, the estimate of ground beef revenue loss from a nationwide recall prompted by pathogen testing was approximately 1.43 million dollars

[38] The source for household population was the U.S. Census Bureau, 2008-2012 American Community Survey 5-Year Estimates. Additionally, we assumed only 63 percent of households consumed packaged ground beef given that only 63 percent of households participating in the IRI Consumer Network purchased packaged ground beef.

or 1.2 percent of monthly industry revenues for packaged ground beef. The loss of ground beef revenues from a ground beef recall prompted by consumer illness investigations was nearly twice as large at approximately 2.44 million dollars or 2.0 percent of monthly industry revenues for packaged ground beef. These estimates represent a lower bound. Actual revenue loss could potentially be much greater if we were to also account for the loss of revenues from random-weight ground beef products and ground beef products sold through other marketing channels (foodservice, institutional, etc.). For comparison, consider that the average amount of ground beef recalled due to STEC contamination between 2008 and 2012 was 296,253 pounds (table 15). At an average price per pound of 3.12 dollars, the direct revenue loss was on average 924,309 dollars per recall, considerably less than the industry retail revenue loss due to decreased demand for packaged ground beef products.

Conclusion

The objective of this analysis was to investigate the impact of food safety information on the demand for ground beef and to determine whether consumers respond differently to varying levels of information. Analyzing disaggregated household purchase data and FSIS recall data, the results reveal that recall events did in fact have a significant impact on packaged ground beef consumption, though the impact was small relative to price and demographic factors. Specifically, a recall prompted by pathogen testing had a negative and significant impact on the likelihood of purchasing ground beef and the impact persisted for a month. A recall prompted by a consumer illness investigation also had a negative and significant impact on the likelihood of purchasing ground beef, but the magnitude of impact was greater and persisted for three months.

As in the previous chapter, the present study takes full advantage of the inherent temporal and geographic variability of ground beef recall events by analyzing disaggregated household data. That is, the study addresses the regional nature of most recall events by identifying and analyzing the purchases of households in the geographic regions under recall advisories as compared to the rest of the nation, and the study addresses the immediate short-run impacts of recall events by analyzing monthly household purchases. Additionally, the study considers possible household heterogeneity by including recall interaction terms with household income and composition, and the results reveal that all households were significantly affected by recall events to a certain extent.

Perhaps the most important contribution of this analysis to the existing literature, however, is the differentiation between recalls prompted by consumer illness investigations and recalls prompted by laboratory testing. As modeled in Chapter III, consumers update their perceptions of risk and their decision rules based on information received through external signals. The strength of the signal and the information conveyed affects the magnitude of the demand impacts and the length of time for recovery, and stronger signals have greater demand impacts and longer recovery periods. Ground beef recalls provide a natural case study to empirically test the impact of varying signal strength as there is sufficient variation in the information conveyed regarding health risk discovery, while maintaining constant the actual health risk and risk severity. That is, of the 58 Class I ground beef recall events due to STEC contamination, 17 were the result of a consumer illness investigation and 41 were the result of pathogen discovery through laboratory testing. The results from the analysis reveal that recalls prompted by consumer illness investigations had a greater and longer-lasting impact on consumer purchases decisions than recalls prompted by pathogen testing, suggesting that consumers perceive recalls with confirmed reports of foodborne illnesses to be stronger information signals than recalls following laboratory tests.

Despite the removal of contaminated ground beef products from the marketplace, consumers responded to recall events by deciding not to purchases ground beef in the weeks and months immediately following the recall event. Consumers used recall events to gauge product quality and safety, and the information contained within the recall announcement was used to evaluate potential risk. Recalls prompted by foodborne illness outbreaks communicated a greater risk to consumers than recalls prompted by laboratory testing. This translates to lost sales for all ground beef producers, not just the firm liable for the contaminated product. Thus, increased protection against bacterial contamination to ensure that fewer recalls occur may have the potential to benefit both consumers and the industry.

Concluding Thoughts

The presence of unsafe foods in markets is primarily the result of imperfect information. Without perfect information, consumers cannot differentiate products based on health risks and producers lose incentive to follow safe production practices because they cannot price products to account for the additional expense of implementing these safe practices. Therefore, the federal government must take measures to ensure that the nation’s food supply is safe by engaging in preventive actions to protect consumers, including overseeing the recall of risky products from the marketplace. The primary objective of this dissertation was to provide an in-depth exploration of the trends and demand impacts of food product recalls. Insights from this investigation may provide targets for both manufacturer food safety practices and regulatory oversight. Moreover, any information regarding changes in consumer behavior in response to food safety risks is of valuable interest to both producers and regulators of the industry in order to determine the welfare benefits associated with increased food safety measures.

The first chapter analyzed trends and patterns in food product recall events from 2004 to 2013. During the course of the decade, food product recall events increased by 10.1 percent a year, with recall events increasing across several major aggregate food categories and across every risk class. Additionally, the results highlighted the extensive impact of ingredient-driven recalls on downstream manufacturers and the significant increase in recalls due to undeclared allergens. The second chapter reviewed the extensive literature on the impact of food safety information on consumer demand. For the most part, the existing literature is comprised of analyses of media indices, singular events, and aggregate data, whereas the present case studies analyzed disaggregated household purchase data and clearly delineated multiple recall events. The third chapter developed a general model to illustrate how consumers form perceptions of risk based on personal experiences and external signals, such as recall events, and how perception of risk in turn impacts demand. The model further established predictions with regards to signal strength and the magnitude and duration of the impact. The final two chapters present case studies that empirically tested these predictions. Specifically, the fourth chapter estimated the impact of leafy green recall events on the demand for packaged leafy green products. The results of several binary response model estimations suggest that iceberg and romaine recall events negatively impacted demand for the implicated leafy green in the weeks immediately following the recall. The fifth chapter estimated the impact of STEC-contaminated ground beef recall events on the demand for ground beef products, differentiating between recalls prompted by consumer illness investigations and those prompted by laboratory testing. The results suggest that the impacts of recalls prompted by consumer illnesses outbreaks are often greater and last longer than the impacts of recalls prompted by pathogen testing.

While the research presented here sheds considerable light on the trends and demand impacts of food product recalls, it is clear that considerable work remains. For one, there is clear need for work exploring the benefits, costs, and impacts of allergen labeling. As illustrated in the first chapter, there has been a significant increase in the prevalence of reported food allergies and the number of recalls due to undeclared allergens, yet very little is known about the economic consequences. Second, with regards to consumer demand and food product recalls, there exists little empirical work that differentiates between the impact of commodity-wide demand and brand-specific demand. This distinction is of particular importance because economic theory regarding traceability, liability, and collective reputation posits that consumers may respond to brand-specific recalls by avoiding implicated brands rather than the commodity as a whole if they believe the health risk to be specific to the firm and not the whole commodity. Lastly, on the supply side, there exists very little knowledge regarding the impact of food product recalls on producer behavior and incentives to adopt safe production practices. In this regard, the dataset of FDA and FSIS recalls developed for the first chapter may prove to be a valuable asset for performing a supply-side analysis.

Appendices

Appendix A. Food Product Recall Categorization

Food Categories	
Grains	**Other or Mixed Vegetables**
Breads (Bread, Pita, Bagels, Tortilla, Crumbs)	Fresh
Rice and Pasta	Frozen
Breakfast Cereal	Prepared
Flour, Bread Mixes, Dough	Dried
Snacks	**Sprouts**
Cake and Baking Mixes	**Fresh Herbs**
Baked Goods (incl. Packaged)	**Vegetable Juices**
Fungi	**Fruit**
Fresh	Fresh
Canned	Frozen
Prepared	Canned/Bottled
Dried	Dried
Leafy Vegetables	**Fruit Juices**
Fresh	**Dairy**
Frozen	Milk
Canned	Cream
Prepared	Yogurt
Dried	Cheese
Root Vegetables	Processed Cheese Products and Sauces
Fresh	Dairy Desserts (e.g. Ice Cream, Pudding, etc.)
Frozen	**Beef**
Canned	Fresh
Prepared	Frozen
Dried	Cooked (Refrigerated/Frozen)
Vine-Stalk Vegetables	**Pork**
Fresh	Fresh
Frozen	Frozen
Canned	Cooked (Refrigerated/Frozen)
Prepared	**Game/Lamb/Other Meat**
Dried	Fresh
Beans, Lentils, Peas, and Legumes	Frozen
Fresh/Dried	**Poultry**
Frozen	Fresh
Canned	Frozen
Prepared	Canned
	Cooked (Frozen/Refrigerated)

Appendix A. Food Product Recall Categorization (cont.)

Food Categories	
Bacon, Sausage, and Lunch Meats	Other Foods
Fish	Fats and Oils
Fresh	Salad Dressing
Frozen	Gravies, Sauces, Condiments
Canned or Packaged	Spices/Seasonings
Dried	Nutrition Bars
Smoked	Baby Formula and Food
Crustaceans	*Sweets*
Fresh	Sweeteners
Frozen	Jellies/Jams/Preserved Fruit
Canned or Packaged	Candy
Mollusks	*Soups*
Fresh	Soups, Ready-to-Serve, Condensed, Bases
Frozen	Soups, Dry
Canned or Packaged	*Prepared Meals*
Nuts and Seeds	Ready-to-Eat
Nuts, Seeds, and Nut Mixes	Ready-to-Eat Sandwiches
Processed Nuts and Seeds (e.g., Nut Butters)	Ready-to-Eat Salads with Greens
Eggs and Egg Mixtures	Frozen or Refrigerated (Ready-to-Heat)
Tofu and Meat Substitutes	Canned or Packaged (Shelf Stable)
Beverages	
Coffee	
Tea	
Carbonated	
Non-Carbonated	
Alcohol	
Water	
Beverage Mix	

Appendix B. Estimated Fixed Effects LPM Coefficients for Leafy Green Demand with Publicized (P) and Non-Publicized (NP) Recall Events

	Romaine	Iceberg	Spinach
Romaine Recall (P)	-0.0017** (0.0006)	-0.0015** (0.0006)	0.0016** (0.0005)
Romaine Recall (NP)	0.0018 (0.0014)	-0.0071** (0.0015)	-0.0018 (0.0012)
Iceberg Recall (P)	-0.0013 (0.0013)	-0.0088** (0.0013)	-0.0046** (0.0011)
Iceberg Recall (NP)	-0.0028 (0.0038)	0.0081 (0.0042)	-0.0025 (0.0033)
Spinach Recall (P)	0.0017* (0.0007)	-0.0001 (0.0007)	-0.0005 (0.0006)
Spinach Recall (NP)	0.0002 (0.0017)	-0.0046** (0.0018)	0.0008 (0.0015)
Price/Oz. Romaine	-0.1347** (0.0134)	0.0650** (0.0146)	0.0319** (0.0113)
Price/Oz. Iceberg	0.0764** (0.0140)	-0.2415** (0.0162)	0.0414** (0.0116)
Price/Oz. Spinach	-0.0149** (0.0055)	0.0112 (0.0059)	-0.0766** (0.0048)
Constant	0.1504** (0.0040)	0.1769** (0.0045)	0.0932** (0.0034)
Household Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Households	94,763	94,763	94,763
Observations	3,304,065	3,304,065	3,304,065
R-squared	0.3159	0.3063	0.2823

Notes: Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively.

Appendix C. Estimated Coefficients for Combined Leafy Green Demand

	LPM OLS	LPM FE	RE Probit	FE Logit
Leafy Green Recall	-0.0020** (0.0008)	-0.0013 (0.0007)	-0.0049 (0.0026)	-0.0087 (0.0045)
Price/Oz. Leafy Green	-0.5568** (0.0322)	-0.3012** (0.0206)	-1.3290** (0.0579)	-2.0183** (0.1084)
HH Income $0-$14,999	-0.0521** (0.0043)	--	-0.1862** (0.0149)	--
HH Income $15,000-$24,999	-0.0417** (0.0039)	--	-0.1425** (0.0132)	--
HH Income $25,000-$34,999	-0.0294** (0.0037)	--	-0.1011** (0.0122)	--
HH Income $35,000-$49,999-	-0.0092** (0.0036)	--	-0.0359** (0.0113)	--
HH Income $60,000-$69,999	0.0068 (0.0043)	--	0.0193 (0.0134)	--
HH Income $70,000-$99,999	0.0222** (0.0035)	--	0.0737** (0.0110)	--
HH Income $100,000+	0.0317** (0.0037)	--	0.1032** (0.0115)	--
HH Size 1	-0.0473** (0.0023)	--	-0.1798** (0.0080)	--
HH Size 3	0.0128** (0.0030)	--	0.0478** (0.0092)	--
HH Size 4	0.0260** (0.0037)	--	0.0868** (0.0115)	--
HH Size 5	0.0283** (0.0052)	--	0.0980** (0.0162)	--
HH Size 6	0.0277** (0.0076)	--	0.1181** (0.0234)	--
HH Size 7	0.0464** (0.0125)	--	0.1267** (0.0370)	--
HH Size 8	0.0435** (0.0163)	--	0.1400** (0.0480)	--
Child $0 \leq$ Age < 6	-0.0256** (0.0043)	--	-0.0591** (0.0140)	--
Child $6 \leq$ Age < 13	-0.0195** (0.0035)	--	-0.0543** (0.0108)	--
Child $13 \leq$ Age < 18	0.0029 (0.0034)	--	0.0184 (0.0105)	--
Constant	0.4398** (0.0076)	0.3839** (0.0046)	-0.2841** (0.0159)	--
Month Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Households	94,763	94,763	94,763	88,257
Observations	3,305,078	3,305,078	3,305,078	3,140,694
R-squared	0.0110	0.2953	--	--
Log Likelihood	--	--	-1,630,067	-1,331,339

Notes: Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively. Household income and size variables are relative to the median household of two persons and an income of $50,000-$59,999.

Appendix D. Estimated Coefficients for Leafy Green Demand

	Romaine				Iceberg			
	LPM OLS	LPM FE	RE Probit	FE Logit	LPM OLS	LPM FE	RE Probit	FE Logit
Romaine Recall	-0.0012*	-0.0016**	-0.0093*	-0.0196**	-0.0042**	-0.0019**	-0.0161**	-0.0295**
	(0.0006)	(0.0006)	(0.0040)	(0.0074)	(0.0006)	(0.0006)	(0.0039)	(0.0071)
Iceberg Recall	-0.0018	-0.0015	-0.0143	-0.0231	-0.0042**	-0.0082**	-0.0465**	-0.0808**
	(0.0013)	(0.0013)	(0.0094)	(0.0173)	(0.0014)	(0.0013)	(0.0091)	(0.0165)
Spinach Recall	0.0014	0.0017*	0.0126**	0.0228**	-0.0035**	0.0001	-0.0013	0.0026
	(0.0008)	(0.0007)	(0.0051)	(0.0093)	(0.0008)	(0.0007)	(0.0050)	(0.0091)
Price/Oz. Romaine	-0.4239**	-0.1349**	-1.4564**	-1.8978**	0.2282**	0.0659**	0.6103**	0.8049**
	(0.0233)	(0.0134)	(0.0780)	(0.1523)	(0.0249)	(0.0146)	(0.0715)	(0.1370)
Price/Oz. Iceberg	-0.0505*	0.0763**	0.3139**	0.9963**	-0.3569**	-0.2410**	-1.5276**	-2.9175**
	(0.0230)	(0.0140)	(0.0737)	(0.1420)	(0.0257)	(0.0162)	(0.0695)	(0.1347)
Price/Oz. Spinach	-0.0313**	-0.0150**	-0.1520**	-0.2048**	-0.0589**	0.0110	0.0084	0.0849
	(0.0099)	(0.0055)	(0.0334)	(0.0629)	(0.0101)	(0.0059)	(0.0309)	(0.0574)
HH Income \$0-\$14,999	-0.0402**	--	-0.3695**	--	0.0038	--	0.1085**	--
	(0.0030)		(0.0201)		(0.0034)		(0.0183)	
HH Income \$15,000-\$24,999	-0.0354**	--	-0.2961**	--	0.0084**	--	0.1240**	--
	(0.0027)		(0.0177)		(0.0031)		(0.0163)	
HH Income \$25,000-\$34,999	-0.0223**	--	-0.1810**	--	0.0050	--	0.0789**	--
	(0.0027)		(0.0162)		(0.0030)		(0.0151)	
HH Income \$35,000-\$49,999	-0.0096**	--	-0.0877**	--	0.0079**	--	0.0672**	--
	(0.0026)		(0.0149)		(0.0028)		(0.0140)	
HH Income \$60,000-\$69,999	0.0108**	--	0.0700**	--	-0.0051	--	-0.0431**	--
	(0.0032)		(0.0175)		(0.0033)		(0.0167)	
HH Income \$70,000-\$99,999	0.0217**	--	0.1610**	--	-0.0080**	--	-0.0720**	--
	(0.0026)		(0.0144)		(0.0027)		(0.0137)	
HH Income \$100,000+	0.0415**	--	0.2725**	--	-0.0323**	--	-0.2508**	--
	(0.0028)		(0.0150)		(0.0028)		(0.0144)	
HH Size 1	-0.0207**	--	-0.1227**	--	-0.0352**	--	-0.2615**	--
	(0.0016)		(0.0106)		(0.0018)		(0.0100)	
HH Size 3	-0.0040	--	-0.0192	--	0.0238**	--	0.1464**	--
	(0.0022)		(0.0121)		(0.0024)		(0.0114)	
HH Size 4	0.0035	--	0.0295*	--	0.0375**	--	0.2314**	--
	(0.0028)		(0.0150)		(0.0030)		(0.0142)	
HH Size 5	0.0034	--	0.0116	--	0.0475**	--	0.3037**	--
	(0.0039)		(0.0213)		(0.0042)		(0.0200)	
HH Size 6	0.0002	--	-0.0107	--	0.0555**	--	0.3855**	--
	(0.0056)		(0.0310)		(0.0063)		(0.0288)	
HH Size 7	-0.0070	--	-0.1064*	--	0.0836**	--	0.4865**	--
	(0.0091)		(0.0495)		(0.0104)		(0.0452)	
HH Size 8	-0.0100	--	-0.0702	--	0.0875**	--	0.4573**	--
	(0.0108)		(0.0642)		(0.0147)		(0.0589)	
Child $0 \leq$ Age < 6	-0.0080*	--	-0.0131	--	-0.0352**	--	-0.1946**	--
	(0.0033)		(0.0185)		(0.0033)		(0.0176)	
Child $6 \leq$ Age < 13	-0.0051*	--	-0.0017	--	-0.0254**	--	-0.1456**	--
	(0.0026)		(0.0142)		(0.0027)		(0.0135)	
Child $13 \leq$ Age < 18	0.0010	--	0.0241	--	0.0003	--	0.0035	--
	(0.0025)		(0.0137)		(0.0028)		(0.0129)	
Constant	0.2404**	0.1505**	-1.2895**	--	0.1817**	0.1767**	-1.2847**	--
	(0.0070)	(0.0040)	(0.0259)		(0.0076)	(0.0045)	(0.0240)	
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Households	94,763	94,763	94,763	57,946	94,763	94,763	94,763	63,948
Observations	3,304,065	3,304,065	3,304,065	2,176,205	3,304,065	3,304,065	3,304,065	2,388,717
R-squared	0.0101	0.3159	--	--	0.0071	0.3063	--	--
Log Likelihood	--	--	-898,482	-684,075	--	--	-1,015,083	-783,464

Note:Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively. Household income and size variables are relative to the median household of two persons and median income of \$50,000-\$59,999.

Appendix D. Estimated Coefficients for Leafy Green Demand (cont.)

	Spinach			
	LPM OLS	LPM FE	RE Probit	FE Logit
Romaine Recall	0.0027** (0.0005)	0.0015** (0.0005)	0.0174** (0.0046)	0.0303** (0.0087)
Iceberg Recall	-0.0060** (0.0011)	-0.0045** (0.0011)	-0.0470** (0.0108)	-0.0873** (0.0202)
Spinach Recall	-0.0008 (0.0007)	-0.0005 (0.0006)	-0.0051 (0.0058)	-0.0094 (0.0110)
Price/Oz. Romaine	0.0304 (0.0190)	0.0322** (0.0113)	0.1874* (0.0884)	0.5154** (0.1786)
Price/Oz. Iceberg	-0.0157 (0.0184)	0.0418** (0.0116)	0.2934** (0.0851)	0.8630** (0.1703)
Price/Oz. Spinach	-0.0810** (0.0078)	-0.0765** (0.0048)	-0.8346** (0.0385)	-1.5418** (0.0750)
HH Income $0-$14,999	-0.0288** (0.0023)	--	-0.3693** (0.0216)	--
HH Income $15,000-$24,999	-0.0256** (0.0021)	--	-0.3044** (0.0190)	--
HH Income $25,000-$34,999	-0.0206** (0.0020)	--	-0.2279** (0.0173)	--
HH Income $35,000-$49,999	-0.0101** (0.0020)	--	-0.1053** (0.0159)	--
HH Income $60,000-$69,999	0.0027 (0.0024)	--	0.0415* (0.0187)	--
HH Income $70,000-$99,999	0.0160** (0.0020)	--	0.1539** (0.0153)	--
HH Income $100,000+	0.0329** (0.0022)	--	0.3121** (0.0159)	--
HH Size 1	-0.0062** (0.0013)	--	-0.0560** (0.0112)	--
HH Size 3	-0.0037* (0.0017)	--	-0.0219 (0.0129)	--
HH Size 4	-0.0053** (0.0021)	--	-0.0497** (0.0161)	--
HH Size 5	-0.0111** (0.0029)	--	-0.0900** (0.0230)	--
HH Size 6	-0.0143** (0.0040)	--	-0.1090** (0.0332)	--
HH Size 7	-0.0128 (0.0069)	--	-0.1401** (0.0529)	--
HH Size 8	-0.0191* (0.0081)	--	-0.1451* (0.0690)	--
Child $0 \leq$ Age < 6	0.0064** (0.0025)	--	0.1150** (0.0195)	--
Child $6 \leq$ Age < 13	0.0049** (0.0020)	--	0.0585** (0.0152)	--
Child $13 \leq$ Age < 18	0.0013 (0.0019)	--	0.0086 (0.0147)	--
Constant	0.0103** (0.0055)	0.0930** (0.0034)	-1.8227** (0.0291)	--
Month Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Households	94,763	94,763	94,763	46,042
Observations	3,304,065	3,304,065	3,304,065	1,756,578
R-squared	0.0077	0.2823	--	--
Log Likelihood	--	--	-673,424	-497,108

Note:Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively. Household income and size variables are relative to the median household of two persons and median income of $50,000-$59,999.

Appendix E. Estimated Coefficients for Ground Beef Demand

	LPM OLS	LPM FE	RE Probit	FE Logit
Consumer Illness Recall	-0.0051** (0.0008)	-0.0036** (0.0008)	-0.0208** (0.0037)	-0.0348** (0.0066)
Pathogen Testing Recall	-0.0104** (0.0011)	-0.0021* (0.0013)	-0.0166** (0.0047)	-0.0201* (0.0085)
Price/Oz. Ground Beef	-0.9335** (0.0242)	-0.1637** (0.0186)	-1.6847** (0.0662)	-1.5599** (0.1304)
HH Income $0-$14,999	0.0225** (0.0039)	--	0.1070** (0.0143)	--
HH Income $15,000-$24,999	0.0155** (0.0036)	--	0.0779** (0.0128)	--
HH Income $25,000-$34,999	0.0133** (0.0034)	--	0.0613** (0.0118)	--
HH Income $35,000-$49,999	0.0067* (0.0031)	--	0.0343** (0.0110)	--
HH Income $60,000-$69,999	-0.0049 (0.0037)	--	-0.0136 (0.0131)	--
HH Income $70,000-$99,999	-0.0114** (0.0031)	--	-0.0530** (0.0108)	--
HH Income $100,000+	-0.0330** (0.0031)	--	-0.1480** (0.0115)	--
HH Size 1	-0.0588** (0.0019)	--	-0.2650** (0.0082)	--
HH Size 3	0.0410** (0.0027)	--	0.1660** (0.0088)	--
HH Size 4	0.0576** (0.0034)	--	0.2342** (0.0109)	--
HH Size 5	0.0741** (0.0050)	--	0.2855** (0.0152)	--
HH Size 6	0.0721** (0.0070)	--	0.2834** (0.0215)	--
HH Size 7	0.0859** (0.0115)	--	0.3285** (0.0336)	--
HH Size 8	0.0980** (0.0156)	--	0.3809** (0.0437)	--
Child $0 \leq$ Age < 6	-0.0192** (0.0042)	--	-0.0516** (0.0136)	--
Child $6 \leq$ Age < 13	-0.0039 (0.0033)	--	-0.0053 (0.0102)	--
Child $13 \leq$ Age < 18	0.0055 (0.0031)	--	0.0279** (0.0098)	--
Constant	0.3678** (0.0055)	0.2292** (0.0036)	-0.6576** (0.0159)	--
Month Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Households	67,446	67,446	67,446	67,174
Observations	2,446,036	2,446,036	2,446,036	2,440,807
R-squared	0.0163	0.2418	--	--
Log Likelihood	--	--	-985,861	-793,279

Notes: Asterisk (*) and double asterisk (**) indicate significance at the five and one percent level, respectively. Household income and size variables are relative to the median household of two persons and an income of $50,000-$59,999.

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