ABSTRACT

Title of dissertation: ESSAYS ON QUALITY CERTIFICATION IN FOOD AND AGRICULTURAL MARKETS

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This dissertation features three essays exploring the market impacts of two types of quality certification—a voluntary non-GMO label and a mandatory food safety standard. In the first essay, I use a hedonic framework to examine whether firms use a voluntary quality certification for non-GMO products to extract rent from customers. Using U.S. retail scanner data coupled with data from a voluntary non-GMO label, I find no evidence of price premiums or quantity changes for newly certified non-GMO products. Instead, the label may induce firms to develop new non-GMO products targeted to high-valuation consumers. The second essay examines how voluntary non-GMO food labeling impacts demand in the ready-to-eat [RTE] cereal industry. I estimate a discrete-choice, random coefficients logit demand model using monthly data for 50 cereal brands across 100 DMAs. Consumer tastes for the label are widely distributed, and this heterogeneity plays a substantial role in individual choices; but, on average, the non-GMO label has a positive impact on demand. I estimate welfare effects by simulating two labeling scenarios: one in which all brands use the non-GMO label, and one in which no brands use the label.

The simulation results suggest that non-GMO labeling in the RTE cereal industry may improve consumer welfare on average. In the final essay, we use data from an original national survey of produce growers to examine whether complying with the Food Safety Modernization Act's Produce Rule will be prohibitively costly for some growers. We examine how food safety measure expenditures required by the Rule vary with farm size and practices using a double hurdle model to control for selectivity in using food safety practices and reporting expenditures. Expenditures per acre decrease with farm size, and growers using sustainable farming practices spend more than conventional growers on many food safety practices. We use our estimates to quantify how the cost burden of compliance varies with farm size. We also explore the policy implications of exemptions to the Rule by simulating how changes to exemption thresholds might affect the cost burden of each food safety practice on farms at the threshold.

ESSAYS ON QUALITY CERTIFICATION IN FOOD AND AGRICULTURAL MARKETS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2017

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Acknowledgments

The level of support I have received during my graduate study at the University of Maryland, both professionally and personally, cannot be overstated. Each of the members of my dissertation committee has contributed to my success immeasurably. I thank my advisor, Sébastien Houde, for his thoughtful guidance and advice throughout my dissertation work. His patient attitude and encouragement while I explored new ideas and worked to overcome obstacles has made me a better researcher. I am also indebted to Erik Lichtenberg, who has provided me with invaluable mentorship and research opportunities that have led to a very fruitful collaboration over the past three years. I thank Jim Hanson for being a wonderful research collaborator, mentor, and friend throughout my time at Maryland, and I am grateful to Rob Williams for providing countless suggestions in the early stages of my research that helped shape the course of my dissertation. Lastly, I would like to thank Yogesh Joshi for helping me navigate the sea of theoretical work on product differentiation.

I would also like to express appreciation for my fellow graduate students in the Department of Agricultural and Resource Economics for their camaraderie and for their valuable comments on my research during workshops. In particular, my cohort of classmates—Joe, Patrick, Magda, Sarah, Shirley, and Xiaoya—have been a great source of friendship and support.

Additionally, I am truly grateful to the AREC department for providing me with the financial support necessary to conduct my research. The Bruce and Mary

Ann Gardner Dissertation Enhancement Award enabled me to purchase essential data, without which my dissertation would not have been possible. The Non-GMO Project also provided me with data vital to my research, for which I thank them.

Lastly, I thank my parents, Varsha and Ashok, as well as my siblings, Anita and Amesh, for their endless support and encouragement, not only during my graduate study, but throughout my life. I also thank my wife Aparna for being a constant source of happiness and humor in all aspects of my life. And, finally, I owe a debt to my cat Fred for keeping me sane while writing my dissertation.

Table of Contents

List of Tables

List of Figures

Introduction

This dissertation features three essays exploring the market impacts of two types of quality certification—a voluntary non-GMO label and a mandatory food safety standard. Quality certification plays an important role in many industries, especially in markets for credence goods (Darby and Karni 1973) and markets with adverse selection (Akerlof 1970). In these cases, consumers cannot accurately evaluate the quality of goods prior to purchase; therefore, certification can alleviate informational asymmetries between consumers and firms and increase market efficiency (Dranove and Jin 2010).

Many forms of quality certification exist in food and agricultural markets in the U.S., ranging from voluntary disclosure to mandatory standards. In the case of non-GMO food products, certification is based on a voluntary third-party label managed by the Non-GMO Project. The Non-GMO Project began offering non-GMO certification and labeling in 2010 for food products that fall under a 0.9% threshold for GMO[1] presence. Products that obtain the certification feature an easily recognizable label on their package. With regards to produce safety, the

[1] GMO stands for "genetically modified organism" and refers to plants whose genetic material has been altered using genetic engineering techniques, such as recombinant DNA technology. This term is also used to describe agricultural crops produced from seed stock that employs this technology and food products that contain ingredients derived from these crops.

prevailing "certification" is the Produce Rule implementing the Food Safety Modernization Act [FSMA], a mandatory government-based minimum quality standard for growing produce. The Produce Rule requires operational changes to meet standards associated with agricultural water; biological soil amendments; domesticated and wild animals; employee training and health and hygiene; and equipment, tools, buildings, and sanitation. This dissertation explores the economic impact of these two quality certifications. The first two essays examine how the Non-GMO Project Verified certification affects demand for food products, and the third essay examines growers' costs of complying with the Produce Rule.

The first essay investigates whether firms use a voluntary quality certification for non-GMO products to extract rent from consumers. Using weekly retail point-of-sale data from a large sample of supermarkets across the U.S coupled with a unique dataset from the Non-GMO Project, I find no statistically significant price premiums or quantity changes for newly certified non-GMO food products. I, however, find support for the hypothesis that the certification may induce other firm strategies such as new non-GMO product development targeted to specific consumers. Altogether, the findings suggest that certification costs are not passed directly to consumers of existing products that are reformulated to meet the non-GMO certification standard. Instead, firms may pass the costs using newly introduced products.

The second essay builds on the first and investigates the role of voluntary non-GMO food labeling as a non-price marketing strategy in the ready-to-eat [RTE] cereal industry. I estimate a discrete-choice, random coefficients logit demand model with monthly retail point-of-sale data for 50 breakfast cereal brands in 100 DMAs between 2010 and 2014. The results indicate that consumer tastes for the non-GMO label have a wide distribution, and this heterogeneity plays a substantial role in individual choices; but, on average, the non-GMO label has a positive impact on demand. To shed light on the potential welfare effects of non-GMO labeling, I simulate two labeling scenarios in the RTE cereal industry: one in which all brands use the non-GMO label over the entire timeframe of the data, and one in which no brands use the label. The simulation results indicate that non-GMO labeling in the RTE cereal industry may reduce industry profits but improve consumer welfare on average.

The final essay, co-authored with Erik Lichtenberg, addresses concerns raised by small and medium size produce growers that compliance with the FSMA Produce Rule will be prohibitively costly. We use data from an original national survey of fruit and vegetable growers to examine that contention. In particular, we examine how expenditures on food safety measures required by the Produce Rule vary with farm size and farming practices using a double hurdle model to control for selectivity in both using food safety practices and reporting expenditures. We find that expenditures per acre decrease with farm size and that growers using sustainable farming practices spend more than conventional growers on many food safety practices. We use our estimates to quantify how the cost burden of compliance varies with farm size. We then explore the policy implications of exemptions to the Rule by simulating how changes to the exemption thresholds for farm revenue and share of direct sales might affect the cost burden of each food safety practice on farms at the threshold.

Chapter 1: Who Pays for Voluntary Quality Certification? Evidence from the Non-GMO Project Verified Label*

1.1 Introduction

Quality disclosure is an important element of many industries, most notably in markets for credence goods (Darby and Karni 1973) and markets with adverse selection (Akerlof 1970). In both cases, quality certification corrects an informational asymmetry between consumers and firms, enabling consumers to ascertain product quality, which can lead to quality improvements and facilitate vertical sorting (Dranove and Jin 2010). By the same token, depending on market structure, firms may use quality certification to exercise market power and engage in second degree price discrimination and extract rent from consumers (Mussa and Rosen 1978), typically benefiting firms at the expense of consumers. This paper explores the role of voluntary quality certification as a means to exercise such market power, using evidence from a voluntary non-GMO certification in the U.S food industry.

The Non-GMO Project began offering non-GMO certification and labeling in 2010 for food products that fall under a 0.9% threshold for GMO presence. Products

*Nielsen data is provided by the Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen.

that obtain the certification feature an easily recognizable label[2] on their packaging that reads, "Non-GMO Project Verified" (See Figure 1.1). The Non-GMO Project does not restrict the types of products that can be certified, which is to say that a product is eligible for certification regardless of whether or not it contains ingredients for which commercially produced GMO variants currently exists. Furthermore, organic products, which are prohibited from containing GMO ingredients based on the National Organic Program standards, are also eligible for certification. As such, the cost of certification can vary significantly depending the magnitude of product changes required (e.g., product reformulation, sourcing of new ingredients, etc.) to meet the non-GMO certification standard.

The goal of this paper is to first determine whether firms use a voluntary, non-GMO quality certification to extract price premiums[3] or increase market share for newly certified food products, and whether these strategies evolve over time. Specifically, I use a hedonic framework to estimate price premiums and changes to quantity sold for newly certified non-GMO food products using the Non-GMO Project Verified label. The estimation is carried out on a large sample of weekly, product-level retail point-of-sale data for 18 product categories from U.S. supermarkets from 2009 to 2014. The transaction data is coupled with a unique dataset from the Non-GMO Project that contains non-GMO certification dates for products throughout the label's history. I find no evidence of price premiums or changes to quantity sold for newly certified non-GMO food products. I then investigate alter-

[2]Throughout the paper, I use the terms "label" and "certification" interchangeably with regards to the Non-GMO Project verification standard.

[3]Depending on the product, price premiums may reflect pass-through of certification costs, rent extraction, or a combination of both.

native strategies by which firms could extract rent and pass the certification cost to consumers. I find suggestive evidence that the certification may induce firms to develop new non-GMO products for specific types of consumers.

The paper is structured as follows. Section 1.2 provides institutional details and discusses the literature on quality disclosure and labeling as well as previous empirical work on willingness-to-pay for non-GMO products. Section 1.3 presents a simple theoretical model on the economics of labeling to help guide the empirical analysis. Section 1.4 describes the data sources I employ to implement this study. Section 1.5 presents the empirical model for the analysis of non-GMO price premiums and quantities sold, with accompanying results in Section 1.6. Section 1.7 explores alternative strategies firms may use to extract rent and pass the certification cost to consumers. Lastly, Section 1.8 offers concluding remarks as well as next steps to better understand firm behavior and consumer preferences.

1.2 Background

1.2.1 Institutional Details

In the U.S., over 90% of canola, corn, cotton, soybeans, and sugar beets are GMO.[4] Most GMO seed varieties are modified to carry several input-traits designed to benefit producers, the most common of which are herbicide tolerance[5] and insect

[4]GMO stands for "genetically modified organism" and refers to plants whose genetic material has been altered using genetic engineering techniques, such as recombinant DNA technology. In the literature, this term is used interchangeably with GM ("genetically modified") and GE ("genetically engineered") to describe agricultural crops produced from seed stock that employs this technology and food products that contain ingredients derived from these crops.

[5]Monsanto's "Roundup Ready" seeds for canola, corn, soybeans, and sugar beets are resistant to glyphosate, the active chemical in their popular herbicide Roundup.

resistance.[6] While genetically engineered seeds exist for additional crops and input traits, these crops represent the vast majority of the total area of GMO crop varieties planted in the U.S. Many common ingredients used in processed foods are derived from these GMO crops, such as aspartame, flavorings, high-fructose corn syrup, oils, starches, and various additives and preservatives; and the Grocery Manufacturers Association estimates that 70-80% of food eaten in the U.S. contain GMOs (Bren 2003).

The FDA asserts that approved GMO food products are not significantly different from or less safe than their non-GMO produced counterparts and, thus, do not require additional labeling. Nonetheless, 64 countries around the world require labeling of GMO food, and labeling has become a mainstream debate in the U.S. The U.S. Organic Standard prohibits the use of GMOs, thus providing an indirect form of non-GMO labeling for Organic food products in the U.S., but conventionally-grown food has no such restriction. Nonetheless, a voluntary verification and labeling scheme for non-GMO products called the Non-GMO Project emerged in the U.S. beginning in 2010. As of December 2015, nearly 35,000 products from over 1,900 brands use the label, accounting for over $13.5 billion in annual sales.

Twenty U.S. states introduced mandatory GMO labeling legislation in 2014, by which time mandatory GMO labeling laws had already been passed in Maine, Connecticut, and Vermont. The labeling laws in Maine and Connecticut contained trigger clauses that required additional states to pass similar laws before theirs would

[6] Monsanto seeds for corn, cotton, and soybeans express genes for insecticidal proteins from Bacillus thuringiensis (Bt).

go into effect, but the Vermont law contained no such clause and became effective on July 1, 2016. In the meantime, Congress passed the National Bioengineered Food Disclosure Standard (2016), creating a national mandatory GMO labeling standard. The bill, which became law on July 29, 2016, preempts any mandatory state GMO labeling laws and calls for the creation of a federal labeling standard within two years of its enactment. Notably, the law allows food manufacturers a choice of labeling including on-package text, a symbol, or a digital link (e.g., a QR code) that provides access to an internet website containing information about the product's GMO content (Hall 2016). Critics of the new law insist that the labeling options are too lenient and will allow food manufacturers to hide the GMO content of their products behind a QR code, effectively preventing consumers without smartphones from accessing that information (Lowe 2016).

The institutional incentives for non-GMO food labeling are well established in the economics literature. In the context of information economics, non-GMO food products are differentiated by a vertical process attribute unobservable to the consumer, even after consumption, which makes them a type of credence good (Darby and Karni 1973). The commonly prescribed mechanism for dealing with this information asymmetry is to implement some type of third-party monitoring or labeling, much like the Organic standard (McCluskey 2000). GMO labeling schemes vary across countries, with the U.S.[7] and Canada employing a voluntary non-GMO labeling regime, while the European Union, Australia, New Zealand, and Japan use

[7]In the case of the U.S., mandatory labeling will take effect once rulemaking is finalized for the National Bioenginerred Food Disclosure Act.

a mandatory GMO labeling scheme. The typical economic argument for voluntary labeling is that, in the absence of market failures, this regime yields the socially optimal outcome while avoiding any unnecessary costs to society. One of the arguments commonly promulgated by the food industry against mandatory GMO-labeling is that such a law would cause a large increase in food prices as food manufacturers reformulate their products to be non-GMO to avoid the stigma that a "contains GMO" label would create, which proved to be a very effective argument in defeating a patchwork of state legislation, most notably Prop 37 in California in 2012 (Carter et al. 2012).

As a corollary to such a cost argument, one might also argue that food manufacturers who choose to use a non-GMO label would also increase food prices, passing on the costs associated with ingredient reformulation as well as certification and labeling fees to the consumer. However, if the market for existing products that become non-GMO certified is very price competitive, already commands high-margins, or is subject to low retailer pass-through rates,[8] firms may not necessarily be able to pass these costs on to consumers. Despite these limitations, if firms can increase market share by adopting the label, incentives may still exist to seek out non-GMO certification. On the other hand, firms may have an opportunity to use new product development as a means to extract a non-GMO price premium. That is, food manufacturers may certify new products prior to market entry and launch at a higher price point. In this case, we may observe firms behaving more strategically,

[8] Besanko et al. (2005) analyze retailer's pass-through behavior of a major U.S. supermarket chain for 78 products across 11 categories and find that pass-through varies substantially across products and across categories.

choosing to price non-GMO products certified within their product life differently from new products certified before market entry. In this paper, my empirical analysis focuses primarily on the first group—products certified within their product life—but I also provide some descriptive analysis to help characterize the second group of products.

1.2.2 Non-GMO Project Verification

The Non-GMO Project is a nonprofit organization that offers third-party verification and labeling for products that fall under a 0.9% threshold for GMO presence, which aligns with the mandatory labeling standards in Europe. The Non-GMO Project Standard defines the program's core requirements including traceability, segregation, and testing of high-risk ingredients at critical control points (Non-GMO Project 2014c). The verification process is handled by one of three technical administrators: FoodChainID, NSF International, and IMI Global. Products that contain any high GMO risk ingredients[9] require an onsite inspection for verification, whereas products with low-risk ingredients may only require a review of the ingredient specification sheets, and therefore verification costs can vary considerably between products (Non-GMO Project 2014a). The Non-GMO Project Standard also requires ongoing testing of all at-risk ingredients[10] as well as rigorous traceability

[9] The Non-GMO Project classifies the following crops as high GMO risk: alfalfa, canola, corn, cotton, papaya, soy, sugar beets, and zucchini and yellow summer squash. Inputs derived from these crops and animals fed these crops or their derivatives are also considered high-risk. They also maintain a list of monitored crops for which suspected or known incidents of accidental comingling have occurred that are regularly tested (Non-GMO Project 2014e).

[10] The Non-GMO Project Standard requires testing of individual ingredients, not finished products, because the latter is not a reliably accurate measure of GMO presence (Non-GMO Project 2014c).

and segregation practices, both of which are maintained through annual audits and on-site inspections for high-risk products (Non-GMO Project 2014b). On average, the verification process takes 4 to 6 months, and upon completion the Non-GMO Project provides the producer with a licensing agreement to use their name and verification mark on the verified product.

The Non-GMO Project also verifies products for which no commercially produced GMO variant currently exists, which they refer to as low-risk. Their rationale for doing so involves four distinct considerations (Non-GMO Project 2014d): (1) Some low-risk products may still contain high-risk ingredients, such as the oil sometimes used in packaged dried fruit; (2) Incidents of accidental comingling of GMO material have occurred with seemingly low-risk products such as rice and flax, so verification can help mitigate these issues; (3) The organization believes that only verifying high-risk products may place a large burden on consumers to know which products are at risk of containing GMO ingredients, and this lack of understanding may provide an unfair marketing advantage to products with high-risk ingredients carrying the label; and (4) The organization believes that verifying low-risk products helps raise awareness and build consumer interest for non-GMO food products as a whole, which can help set norms as new GMO products are developed.

Usage of the Non-GMO Project Verified label has grown significantly over the past five years, with sales of labeled products in 2014 totaling $11 billion (Non-GMO Project 2014a). Figure 1.2 shows the monthly cumulative growth in products using the label by Organic status. The label launched with about 200 products in 2010 and includes over 15,000 products as of January 2015. Products using the label are close to evenly split between Organic and conventionally grown. Non-GMO Project Verified products span a wide range of product categories as well. Figure 1.3 shows the annual growth by product category for products using the label. As of December 2014, the largest category was snack foods, desserts, and sweeteners, accounting for over 2,800 products. Other large categories include beverages; breads, grains, and beans; fruits and vegetables; and packaged/prepared foods, each of which comprises over 1,500 products.

As of 2015, the Non-GMO Project Verified program accounts for the largest share of non-GMO food labeling in the U.S., but in recent years other voluntary labeling efforts have also emerged. Whole Foods Market, the top specialty grocer in the U.S., has vowed to label all GMO products in their stores by 2018, and the FDA recently finalized their industry guidance for voluntary non-GMO labeling (FDA 2015). In May 2015, at the request of a major non-GMO grain dealer in the U.S., the USDA developed a voluntary non-GMO certification and labeling program through their existing "USDA Process Verified" program (Jalonick 2015). Similar to other USDA-sponsored voluntary food labels such as "humanely raised" or "grass fed", the program is administered through the department's Agriculture Marketing Service and is available to companies for a paid fee. Also in mid-2015, NSF International launched another private label option called the Non-GMO True North program, which offers certification and labeling of non-GMO intermediate and retail products (Greene et al. 2016).

1.2.3 Relevant Literature

The concept of a credence good was first discussed by Darby and Karni (1973) as an extension of search and experience goods (Nelson 1970). In the context of a vertically differentiated good,[11] the consumer knows what she needs *ex ante*, but she neither observes the utility nor the type of good she receives *ex post*. Because consumers cannot verify quality even after consumption, a market for credence goods will theoretically fail in the absence of third-party monitoring.

More broadly, credence goods are simply a manifestation of asymmetric information between consumers and producers, a topic widely discussed in the literature on quality disclosure. Perhaps the most fundamental and oft-cited result in this area is the well-known "unraveling result" (Viscusi 1978; Grossman 1981). According to the theory, all but the lowest quality seller in a market have an incentive to voluntarily disclose quality information, thus eliminating the need for mandatory disclosure. However, this result is based on several strong assumptions, so in reality, we observe incomplete voluntary disclosure in many markets.[12] Milgrom and Roberts (1986) show that if the consumer is unsophisticated or not well informed, full voluntary disclosure will generally fail. This is particularly applicable to non-GMO labeling given that genetic engineering is a relatively new technology, and the average consumer may be unaware of its proliferation in the conventional food system. Another important consideration is interactions between different quality

[11] In the case of non-GMO food products, this vertical differentiation takes the form of a process attribute.

[12] For an extensive review of the literature on the failure of unraveling and, more broadly, on the theory and practice on quality disclosure, see Dranove and Jin (2010).

labels (e.g., interaction between Organic and non-GMO food labels). Bonroy and Constantatos (2014) review the theoretical literature on quality labels and discuss how a new label may interact with existing market distortions, identifying a number of effects that may cause the industry not to set a socially optimal label. From a relevant policy perspective, Roe and Sheldon (2007) examines the tradeoffs between different labeling regimes (private versus government, discrete versus continuous quality, mandatory versus voluntary) and shows that firms tend to prefer discrete labels certified by private firms.

Most empirical studies of GMO labeling employ hypothetical surveys and incentivized lab experiments to analyze consumer preferences for GMO products. Lusk et al. (2005) identifies 25 separate studies that together provide 57 estimates of consumers' willingness-to-pay (WTP) for GMO food products. Significant variation exists in the valuation estimates across studies. Percentage premiums for non-GMO food ranged from -68% to 784%, with an average of 42%, and are significantly affected by elicitation method.

More recent studies tend to focus on the issue of GMO labeling more directly and attempt to quantify the effects of different labels. Onyango et al. (2006) uses a nationwide survey to analyze U.S. consumer's choice of cornflakes in five different labeling scenarios. They find that consumers place a 10% premium on food labeled as non-GMO and 6.5% discount on food labeled as GMO; but, interestingly, consumers also attach a 5% premium for food labeled GMO if the label also specifies "USDA approved" or "to reduce pesticide residues in your food." Roe and Teisl (2007) further explores the nuances of GMO labeling content by eliciting consumer reactions to 80 different GMO label variations through a survey. A key finding of the study is that labels with simple claims and claims certified by the FDA are most credible. Dannenberg et al. (2011) uses an experimental auction to compare mandatory versus voluntary labeling of GMO food and finds that when two labels exist, one for GMO and one for non-GMO, both schemes generate a similar level of uncertainty about unlabeled products. Costanigro and Lusk (2014) conducts a series of choice experiments and finds evidence that consumer WTP to avoid GMO food is 140% higher with a mandatory "contains" GMO label compared to a voluntary "does not contain" GMO label.

1.3 Economics of Voluntary Non-GMO Food Labeling

Food products tend to be differentiated both horizontally and vertically in product space. The vertical dimension reflects quality-based attributes, which share a "more is better" property. Therefore, while consumers may differ in their valuation of quality, these attribute levels can be consistently ranked by all consumers. The horizontal dimension reflects non-quality taste attributes, which each consumer will rank differently based on their taste preferences. For example, nutritional content and freshness could be vertical quality attributes, whereas texture, flavor, and brand could be considered horizontal taste attributes. Given the observed level of segmentation in nearly all food product categories, any realistic model of non-GMO food labeling should account for heterogeneity in consumer preferences along both dimensions. Additionally, in terms of market structure, the food manufacturing industry tends to be dominated by multiproduct firms operating under oligopolistic competition.[13]

1.3.1 Baseline Model

Desai (2001) develops a multiproduct firm duopoly model in which the market consists of two consumer segments that differ in their willingness to pay for quality, and consumers in each segment are distributed across a linear city *a la* Hotelling (1929). Each consumer's location reflects her specific taste preference, and the "transportation cost" for each segment represents that segment's strength of taste preferences. Each firm produces up to two products (one for the low-valuation segment and one for the high-valuation segment), and has a fixed location on the line within a given segment that reflects consumer perceptions of the firm's product taste attributes (i.e. a firm's location may differ across consumer segments). I use this model as a baseline by which to analyze the economics of voluntary non-GMO food labeling and present a summary of its original specification below.

Formally, as presented in Desai (2001), the market consists of a high-valuation and a low-valuation consumer segment ($i = H, L$), each of which contains N_H and N_L consumers, respectively. Consumers in each segment gain utility $\theta_i q$ from consuming a product of quality q. Furthermore, consumers in each segment are uniformly distributed along $[0, 1]$ in a linear city and incur transportation cost k_i to travel away from their location x. As such, a consumer of type i derives utility $U(\theta_i, x) =$

[13] Take, for example, the market for ready-to-eat cereals, in which the top four firms, each producing dozens of different brands, account for upwards of 80% of the market (Nevo 2001).

$\theta_i q - k_i t - p$ from consuming a product of quality q, price p, located a distance t from the consumer's location. The supply side consists of two symmetric firms ($j = A, B$), each of which produces a product of quality q_{ij} for consumer segment i. In each segment i, Firm A is located at a distance a_i, and Firm B is located at a distance b_i from the left,[14] where $a_i < 1/2$ and $b_i = 1 - a_i > 1/2$. Costs are identical across firms, with each firm incurring marginal cost $c(q) = \gamma q^2/2$ for producing a product of quality q. Firms maximize profits by choosing prices (p_{Lj}, p_{Hj}) and quality levels (q_{Lj}, q_{Hj}) for their respective product lines.

In contrast to the classic monopoly self-selection models with only vertical differentiation (Mussa and Rosen 1978; Moorthy 1984), in this model firms provide each segment with its preferred quality level and the typical self-selection constraints are not binding in equilibrium (under some conditions).[15] In this scenario, when both market segments are fully served, the location x_i of the consumer in segment i indifferent between buying products of quality q_{iA} and q_{iB} offered by each firm is

$$x_i = \frac{\theta_i(q_{iA} - q_{iB}) + k_i(a_i + b_i) - (p_{iA} - p_{iB})}{2k_i} \quad \text{if} \quad a_i \leq x_i \leq b_i. \tag{1.1}$$

We can thus calculate demand for each product of Firm A (d_{iA}) and Firm B (d_{iB}) as $d_{iA} = N_i x_i$ and $d_{iB} = N_i(1 - x_i)$, respectively. The equilibrium prices and qualities

[14] See Figure 1 in Desai (2001) for a visual representation of the model.

[15] The appendix in Desai (2001) provides a full derivation of the equilibrium for the duopoly model.

for the unconstrained problem are

$$p_{iA}^* = \frac{1}{6}\left(2k_i(2 + a_i + b_i)\right) + \frac{\theta_i^2}{2\gamma},$$
$$p_{iB}^* = \frac{1}{6}\left(2k_i(4 - a_i - b_i)\right) + \frac{\theta_i^2}{2\gamma}, \quad q_{ij}^* = \frac{\theta_i}{\gamma}, \tag{1.2}$$

and this solution satisfies the self-selection constraints when $-2\gamma[(1 + a_L - a_H)k_H - k_L] + (\theta_H - \theta_L)^2 \geq 0$. Economically, this condition indicates that firms are more likely to provide low-valuation consumers with their preferred quality levels when there is greater heterogeneity in quality valuations than in taste preferences between segments; and firms are more likely to provide efficient quality to the low-valuation segment as horizontal differentiation decreases in the high-valuation segment. Additionally, price-cost margins are increasing in taste preferences k_i; if high-valuation consumers also have stronger taste preferences, the higher quality product will have higher price-cost margins as well.

1.3.2 Introduction of the Non-GMO Label

Within the horizontal or vertical product space, food can have multiple attributes, each of which consumers may value differently. In the baseline model, I represent the attributes within each space as single taste and quality attribute. When thinking about how to model voluntary non-GMO labeling, consider that Non-GMO production is a vertical process attribute that is (weakly) more costly than conventional production, which supports its treatment as a quality attribute in a vertical differentiation framework. Nonetheless, because non-GMO is a credence attribute, it is plausible that some consumers may value it in a fundamentally different way than other quality attributes, thus warranting a separate treatment in the consumer utility function.

Prior to the introduction on the non-GMO label, suppose that consumers derive utility and firms operate in equilibrium as characterized in the baseline model presented in Section 1.3.1.[16] Once the non-GMO label is launched, consumers gain additional benefit from food products that feature the label such that the a consumer of type i derives utility $U(\theta_i, \delta_i, x) = \theta_i q + \delta_i D_{ng} - k_i t - p$, where $D_{ng} = 1$ if a product undergoes non-GMO certification and uses the label, and δ_i is the incremental gain in utility a consumer of type i gets from consuming a non-GMO product.

When a firm chooses to certify an existing product, it necessitates replacing any GMO ingredients in the product with non-GMO variants, which often cost more to produce. I model this new cost as a constant, additive term α in the expression for marginal cost: $c(q, D_{ng}) = \gamma q^2/2 + \alpha D_{ng}$. That said, it is important to note that non-GMO variants do not differ from GMO variants of ingredients nutritionally or in any other way the FDA deems "significant," so this type of "reformulation" is more aptly characterized as simply a re-sourcing of certain inputs and may not induce firms to re-optimize over other quality attributes.[17] Therefore, I assume that quality is fixed at the equilibrium in the baseline model, and firms decide whether or not to label their products by choosing prices to maximize profits given the new consumer utility and marginal cost.

[16]See Appendix A.1 for a brief characterization of the baseline equilibrium.

[17]In fact, if firms did reformulate a product in an appreciable way, resulting in a change of ingredients or nutritional content, this would trigger a new UPC and effectively qualify as a new product.

We can show that if Firm A chooses to label its products and Firm B does not, the consumer indifference location x_i shifts to the right by an amount $\delta_i/2k_i$, enabling Firm A to capture additional market share and make greater profit at Firm B's expense, provided that $\delta_i > \alpha$. By symmetry, the equivalent outcome occurs if Firm B chooses to label and Firm A does not.[18] In equilibrium, both firms' optimal strategy is to label their products, in which case x_i remains unchanged relative to the baseline case due to symmetry across firms, and both firms' prices simply increase by an amount equal to the additional marginal cost α for non-GMO labeling, resulting in no change in profits.[19] Interestingly, in the duopoly setting, neither firm can use the non-GMO label to exercise market power and extract additional rents from consumers due to the nature of competition between the two firms. Additionally, note that if the incremental marginal cost α associated with non-GMO labeling is insignificant, firms may not increase prices at all upon labeling their products. Lastly, due to symmetry of the non-GMO utility term across products of either quality type for a given consumer, the labeling equilibrium will automatically satisfy the self-selection constraints when $-2\gamma[(1 + a_L - a_H)k_H - k_L] + (\theta_H - \theta_L)^2 \geq 0$, as in the baseline equilibrium.

1.3.3 Incentives for New Product Development

In the previous model of non-GMO labeling, I assume that consuming a non-GMO product benefits consumers in either segment i through an incremental gain in

[18] See Appendix A.2 for a complete derivation of the result when only one firm chooses to label its products as non-GMO.

[19] See Appendix A.3 for a derivation of the equilibrium when both firms choose to label their products as non-GMO.

utility δ_i; and once the label launches in the marketplace, firms take quality of their existing product line as fixed from the pre-labeling regime when deciding whether or not to label their products. However, one might argue that a more GMO-attentive consumer segment exists that values the non-GMO label in a fundamentally different way. For this segment of consumers, the benefit of the non-GMO label may interact with the quality and taste dimensions in consumer utility, such that it enhances their valuation of quality or increases the strength of their taste preferences[20]—i.e., brand loyalty.

In this scenario, the label could induce firms to develop new products at the higher, preferred quality level of this segment because doing so would enable firms to extract higher price-cost margins on these products. In effect, the label may serve as a mechanism by which to segment these GMO-attentive customers from other high-valuation consumers and make it more profitable to serve them separately. For the sake of comparability, I build off the same two-segment baseline model presented in Section 1.3.1. Once the non-GMO label is launched, consumers in segment L derive utility $U(\theta_L, \delta_L, x) = \theta_L q + \delta_L D_{ng} - k_L t - p$, just as before. Consumers in segment H derive utility $U(\theta_H, \delta_H, x) = \theta_H(1 + \delta_H D_{ng})q - k_H(1 + \delta_H D_{ng})t - p$, as described above. Marginal costs are $c(q, D_{ng}) = \gamma q^2/2 + \alpha D_{ng}$. Lastly, I assume that quality for products in segment L (i.e. pre-existing products) is fixed at the equilibrium in the baseline model, but firms now choose new optimal quality levels for products in segment H (i.e. new product development), in addition to choosing

[20] Empirical work suggests that not all consumers assign a non-negative valuation to non-GMO certification (Lusk et al. 2005), in which case the non-GMO attribute may not meet the "more is better" property for all consumers, thus warranting its treatment as a horizontal taste attribute.

prices to maximize profits given the new consumer utility and marginal cost. In equilibrium, both firms' optimal strategy is to label their products and increase quality for segment H. The equilibrium prices for products in segment L match those presented in Section 1.3.2, where prices increase by an amount equal to the additional marginal cost α for non-GMO labeling. The equilibrium prices and qualities for products in segment H are

$$\begin{aligned} p_{HA}^* &= \frac{1}{6}\left(2k_H(1+\delta_H)(2+a_H+b_H)\right) + \frac{\theta_H^2(1+\delta_H)^2}{2\gamma} + \alpha, \\ p_{HB}^* &= \frac{1}{6}\left(2k_H(1+\delta_H)(4-a_H-b_H)\right) + \frac{\theta_H^2(1+\delta_H)^2}{2\gamma} + \alpha, \\ q_{Hj}^* &= \frac{\theta_H(1+\delta_H)}{\gamma}. \end{aligned} \tag{1.3}$$

Clearly, in this model the price-cost margins for segment H are amplified by the interaction effect of the non-GMO label with taste preferences in consumer utility. In fact, unlike the previous case, even if both segments have identical transportation costs (i.e. $k_H = k_L$), segment H still commands a higher price-cost margin in this setting. Additionally, we can show that both firms earn additional profit in the amount of

$$\Delta\Pi_j = \frac{N_H k_H \delta_H}{2} \tag{1.4}$$

over the baseline equilibrium and, by extension, the equilibrium in which both firms simply label their pre-existing product line.[21]

[21] See Appendix A.4 for a derivation of the equilibrium when both firms choose to introduce a new product for segment H.

1.4 Data

1.4.1 Nielsen Retail Scanner and Consumer Panel Data

Because the Non-GMO Project Verified label has only been in use since 2010, and the majority of its growth has occurred from 2012 onward, it is crucial that this research is conducted with the most recent demand data available. The Nielsen Retail Scanner (Nielsen RMS) data contains weekly purchase and pricing data from retail store point-of-sale systems for over 2.6 million UPCs. The data includes 35,000 retail stores across the U.S., representing over 90 major retail chains in 52 markets. It includes all 1,100 reported Nielsen product categories, which span 125 product groups and 10 departments. In addition to demand data, the dataset includes store demographics and product characteristics.

The Nielsen Consumer Panel (Nielsen HMS) data contains trip-level purchase and pricing data for an unbalanced panel of 40,000 to 60,000 U.S. households and spans the same timeframe as the Retail Scanner data. The data is collected using a handheld scanning device that participants use at home to track all their purchases. Like the Retail Scanner data, the Consumer Panel data includes all 1,100 reported Nielsen product categories for all major retail channels: grocery, drug, mass merchandise, superstore, club stores, convenience, and health. Along with purchase data, the panel includes consumer demographics, product characteristics, and geographic data.

1.4.2 Non-GMO Project Data

I have secured a unique monthly dataset of verified products from the Non-GMO Project that includes product UPC, verification date, product name, product category, organic status, and producer/brand name. The data spans the entire label history through 2014. I merge this information with Retail Scanner data from Nielsen to clearly identify non-GMO food products that use the Non-GMO Project Verified label. Moreover, the label verification date contained in this dataset allows me to identify when non-GMO products in the Nielsen data began using the Non-GMO Verified label.

1.4.3 Selection of Food Categories

For this analysis, I focus on 18 food product categories primarily consisting of snack foods, dry goods, and other processed foods. Table 1.1 presents summary statistics for each product category of the Nielsen Retail Scanner Data from 2009 to 2014. The decision to focus on these categories is based on common and distinct factors for each category. First, all 18 categories are comprised of a non-negligible share of Organic products. Because Organic products do not contain GMO ingredients, their presence ensures the existence of products that are eligible for non-GMO certification without reformulation within a given food category, and these products may serve as a reliable counterfactual to help identify the effect of non-GMO labeling. Additionally, each category exhibits good variation in non-GMO labeling over time and has exhaustive coverage in the Nielsen data, helping ensure that the empirical analysis will have reasonable identification power to provide meaningful results.

Each category also has unique features that will aid in uncovering nuances in the analysis. Ready to eat cereal has a long history of study in the empirical industrial organization literature, beginning with the work of Scherer (1979) on optimal product variety through the work of Richards and Hamilton (2015) on variety pass-through. This may provide a benchmark for our analysis and help guide future avenues of exploration. Snack chips have distinct varieties that are either more or less likely to contain GMO ingredients, and this feature is likely more salient to consumers than in other product categories. For example, tortilla chips are primarily corn-based. Over 90% of corn in the U.S. is GMO, so these products present a much more salient GMO "risk" to consumers. On the other hand, potato chips are made mostly of potatoes, for which no commercially available GMO varieties currently exist, and thus pose a lower "risk" to consumers.

Baby food represents a product category for which consumers may have a heightened sensitivity to GMO presence; and, therefore, we may expect to see different purchasing behavior in this category. In particular, parents that perceive GMO ingredients as posing some sort of health risk may pay a higher premium for non-GMO in this category, since these food products are intended for their children. On the other hand, baby food has long been dominated by a small number of well-established conventional brands, and the reputations these firms have built over time may overshadow non-GMO labeling. Other product categories pose differing levels of GMO risk as well. For example, products from categories such as rice, chocolate, dried fruit, olive oil, nuts, tea, pasta, and dry seasoning, have no commercially available GMO variants; however, in some cases the additives used in processing may contain GMOs (e.g., soy lecithin used in chocolate, etc.). Lastly, cooking oils are typically made from corn, soybean, and canola, all of which are predominantly GMO in the U.S.

Figure 1.4 shows total national sales for Non-GMO Project Verified products between 2010 and 2014, based on the retail scanner data for the selected product categories. The figure also shows sales of products each year that became Non-GMO Project Verified in a future calendar year, denoted "To Be Verified," which helps distinguish growth in the Non-GMO market from newly introduced products versus existing products that become Non-GMO Project Verified. Sales on Non-GMO Project Verified products more than doubled in 2011 and 2012, largely due to growth in labeling among existing products. 2013 and 2014 also saw double-digit percentage growth, attributable to both expansion of the overall Non-GMO market as well more labeling among pre-existing products.

1.5 Empirical Model

For each product category in the analysis, the Nielsen Retail Scanner Data contains weekly prices and quantities sold across the U.S. at the store and UPC level. For each estimation, I restrict the sample to products that obtained the Non-GMO Project Verified label between 2010 and 2014, with at least 6 months of sales data prior to being certified and 12 months of sales data after certification.[22] The rationale for this approach is based on two requirements. First, the empirical specification relies on pre- and post-treatment indicators that I construct using the product verification dates; therefore, it is critical that sufficient data exists before and after the labeling event to estimate the effect of the label on prices and quantities. Second, the sample needs to remain relatively stable to minimize the confounding effects of product entry and exit on the model estimates. Restricting the sample as I have done helps ensure both these conditions are met.[23]

1.5.1 Price Premium Regression Model

1.5.1.1 Main Specification

I use scanner data from 2009 to 2014 aggregated to the national level and calculate a sales-weighted price per ounce p_{jklt}, where j is a product UPC, k is a manufacturer, l is a category, and t represents a particular week. Using the verification dates for non-GMO products, I construct multiple treatment indicators based on the timeframe before and after a product receives the non-GMO label to estimate the average effect of labeling on prices for non-GMO food products and

[22] As a robustness check, I explore several specifications using the full sample, which includes conventional products that were never certified, and found no significant deviations. Those results are available in Appendix A.5.

[23] As a caveat to the subsequent analysis, note that post-treatment indicators beyond 12 months are subject to changes in product mix.

explore dynamic effects of the label in greater detail,

$$\log(p_{jklt}) = \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \tag{1.5}$$

where each treatment indicator is a dummy variable that equals 1 if observation week t is, respectively, 6 to 12 months prior, 0 to 6 months prior, 0 to 6 months after, 6 to 12 months after, 12 to 24 months after, or greater than 24 months after the verification date for product j; ξ_j, ξ_k, ξ_l, and ξ_t are product UPC, manufacturer, category, and week fixed effects, respectively; and ϵ_{jklt} is a random error term. To control for any potentially confounding manufacturer- and category-level pricing decisions, I allow the weekly intercepts to vary across manufacturer and category by including Week×Manufacturer×Category fixed effects. The coefficients of interest, $\boldsymbol{\psi}$, measure the average price effect of non-GMO labeling in each time period. Since I use a log-linear specification, the coefficients $\boldsymbol{\psi}$ can be interpreted as a percentage change in the product price in each time period.

1.5.1.2 Organic Interaction

The National Organic Program, established in 2000, also prohibits the use of GMO ingredients, effectively making USDA Certified Organic products a subset of Non-GMO products. Therefore, a Non-GMO Project Verified label on an organic product is somewhat redundant and does not necessarily provide new information, so I would not expect to observe a price premium associated with it. Nonetheless, nearly half of all Non-GMO Project Verified products are also Certified Organic, suggesting that firms believe that consumers are not fully informed about the organic standard or that the Non-GMO label bestows some additional value. There may also be favorable cost considerations that influence a firm's decision to seek out a non-GMO label for organic products: firms have already invested in a Non-GMO supply chain and incurred any associated reformulation costs for these products. Furthermore, the supply chain has already been vetted to minimize adventitious presence of GMO ingredients, so the likelihood of incurring any unforeseen costs during the certification process is lower for organic products. Therefore, we expect the cost of non-GMO certification for organic products to be less than that of non-organic products; and, to the extent that certification costs are passed through to the consumer, this will be reflected in price premiums.

Both of these factors support the hypothesis that Certified Organic products will command lower price premiums after non-GMO certification than non-organic products. I explore this with an additional price premium specification that includes an organic indicator interacted with the treatment indicators:

$$\begin{aligned}
\log(p_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\
& + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \psi_7 PRE612_{jklt} \times \mathrm{Org}_j \\
& + \psi_8 PRE06_{jklt} \times \mathrm{Org}_j + \psi_9 POST06_{jklt} \times \mathrm{Org}_j + \psi_{10} POST612_{jklt} \times \mathrm{Org}_j \\
& + \psi_{11} POST1224_{jklt} \times \mathrm{Org}_j + \psi_{12} POST24p_{jklt} \times \mathrm{Org}_j \\
& + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \qquad (1.6)
\end{aligned}$$

where Org_j is an indicator variable that equals one if product j is Certified Organic.

1.5.2 Quantity Regression Model

Depending on market conditions, firms may not be able to extract a price premium by using the label; however, firms may use the non-GMO Project Verified label to capture market share from other products. To test for this possibility, I regress weekly product sales quantities on the treatment indicators using a specification similar to that used for the price premium regressions. I use scanner data from 2009 to 2014 aggregated to the national level and calculate weekly sales quantity q_{jklt},where j is a product UPC, k is a manufacturer, l is a category, and t represents a particular week. I construct the same time-period-based indicator variables based on when a product receives the non-GMO label to estimate the average effect of labeling on the sales quantity for non-GMO food products,

$$\begin{aligned}\log(q_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ & + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \qquad (1.7)\end{aligned}$$

where the treatment indicators are the same as in Equation 1.5; ξ_j is a product UPC fixed effect; and $\xi_t \times \xi_k \times \xi_l$ is a Week×Manufacturer×Category fixed effects. The coefficient of interest, $\boldsymbol{\psi}$, measures the average quantity effect of non-GMO labeling in each time period. Since I use a log-linear specification, the coefficients $\boldsymbol{\psi}$ can be interpreted as a percentage change in the weekly sold quantity in that time period.

1.5.3 Identification

Each of the specifications introduced above includes fixed effects to control for unobserved heterogeneity across product UPC and week-manufactuer-category. The product-UPC fixed effect controls for unobserved differences in product attributes across UPCs. The week-manufacturer-category fixed effects essentially create weekly intercepts to control for manufacturer-category level pricing changes. Therefore, the identification strategy relies on variation in timing of non-GMO certification for UPCs within each manufacturer-category. In other words, if every UPC for a manufacturer-category is certified in the same week, the treatment effect cannot be identified. I provide a measure of this variation in Table 1.2. For each product category, I calculate the average number of weeks between the first and last non-GMO product certification for each manufacturer. With the possible exception of olive oil, there is sufficient variation in certification timing in all product categories for identification. Of course, the standard identifying assumption also applies: unobserved factors that could simultaneously affect price or quantity sold and non-GMO certification are time-invariant.

1.6 Results

1.6.1 Price Premiums

1.6.1.1 Main Results

Table 1.3 presents the price premium regression results based on the model specified in the Equation 1.5. Columns I and II present alternate specifications with a progression of fixed effects, and Column III is the preferred specification. In the first specification with UPC and Week×Category fixed effect, I estimate coefficients for the pre- and post-treatment indicators that are consistently negative and statistically significantly different from zero. The estimates for pre-certification 6-12 months and pre-certification 0-6 months indicate about a 1% decrease in price leading up to the certification event. After certification, the price decreases by about a 3% in the first 0-6 months and becomes more negative over time.[24] In the second specification with UPC and Week×Manufacturer fixed effects, the point estimates for the coefficients are negative as well, but most of them are not statistically significantly different from zero; and, furthermore, the estimates are heavily attenuated. The fact that the Week×Manufacturer fixed effect absorbs much of the significant negative treatment effect observed in the first specification suggests that firms may be engaging in manufacturer-level pricing decisions that were biasing the previous results.

[24] Based on the data construction, the coefficient estimates for the post-certification 12-24 months and 24+ months indicators may be biased by changes in product mix, since the sample only guarantees 12 months of post-certification data for a given UPC.

In the final specification with the full suite of UPC and Week$\times$Category$\times$Manufacturer fixed effects, the treatment effect vanishes, and none of the coefficient estimates are statistically significantly different from zero. Moreover, while the point estimates are still slightly negative, they are further attenuated towards zero and lack economic significance. These results show no evidence of dynamic pricing effects, either; which is to say that the treatment effect does not evolve over the post-certification time period. The progression of results across specifications suggests that firms may engage in manufacturer and category specific pricing strategies; but once we control for this behavior, we do not find evidence that firms are using the Non-GMO Project Verified certification to extract price premiums on pre-existing products.

There are a number of reasons firms may not use the Non-GMO Project Verified label to extract price premiums for existing products, some of which were discussed in prior sections of this paper. The stylized data presented in Section 1.4 suggests that non-GMO food products occupy a higher-priced food segment to begin with, so it is possible that firms already enjoy large profit margins on these product and cannot increase prices without losing market share. Additionally, we observe that a significant portion of Non-GMO Project Verified products receive certification *prior* to market entry, and these products may launch at a higher price point on average, relative to existing Non-GMO Project Verified products. Therefore, another possibility is that firms are recouping costs and exercising market power through new product entry.

1.6.1.2 Organic Interaction Results

Table 1.4 presents the price premium regression results based on Equation 1.6 that includes an organic indicator interaction term with each of the treatment indicators. Once again, Column I and II contain results for an alternate specifications with UPC and Week×Category fixed effects and with UPC and Week×Manufacturer fixed effects, respectively. The preferred specification in Column III employs the full suite of fixed effects from Equation 1.6. The progression of results across specifications is very similar to that presented in the previous section, with the Week×Manufacturer fixed effect absorbing some manufacturer-level pricing behavior in the second specification.

Focusing on the final specification, the main treatment indicator coefficient estimates are not statistically significantly different from zero, and the point estimates are very close to zero, which is consistent with our results from the main specification. To interpret the organic interaction, the coefficient estimates for the main and interaction terms should be added together.[25] The point estimates for the organic interaction terms are all slightly negative, but only the post-certification 12-24 month interaction term is statistically significantly different from zero.[26] Therefore, I cannot conclude that organic products command smaller price premiums for non-GMO certification than non-organic products.

[25]Because I include UPC fixed effects, a separate, time-invariant organic indicator term cannot be estimated.

[26]Given the potentially confounding product mix effects after 12 months of certification, this result warrants some skepticism.

1.6.2 Quantity Sold

While our results do not indicate that firms use the non-GMO certification to extract price premiums for existing products, firms may use the certification to sell more units of non-GMO products. For single-product firms, any increase in quantity sold directly increases profits so long as the product has a positive profit margin. In the case of multi-product firms, if these firms seek non-GMO certification for products that command higher profit margins, then any increased market share for these products will also lead to increased profits.

Table 1.5 presents results for the quantity regression estimates based on Equation 1.7. As with the price premium regressions, Column I, II, and III contain results for a progression of fixed effects, with the preferred specification contained in Column III. In the first specification, the estimates for the post-certification 0-6 months and 6-12 months treatment indicators are positive and statistically significantly different from zero, suggesting that firms may increase quantity sold after certification for non-GMO products. However, to the extent that firms engage in manufacturer-level marketing strategies, this specification will produce biased results. Once we control for Week×Manufacturer fixed effects in the second specification, the results lose statistical significance, although the point estimates are still large and positive. In the preferred specification, while the point estimates for the post-certification treatment indicators remain positive, none of the estimates are statistically significantly different from zero. As such, our results do not provide conclusive evidence that firms use the non-GMO certification to increase the quantity of products sold.

1.7 Alternative Firm Strategies

In the preceding results, I find no evidence that firms use non-GMO certification to extract price premiums or increase quantities sold for pre-existing, newly certified products. The certification may, however, induce other firm strategies such as new non-GMO product development targeted to specific consumers by which firms could extract rent and pass the certification cost to consumers. To explore this possibility, I first show that a significant portion of non-GMO products obtain the Non-GMO Project Verification *prior* to appearing in the retail scanner data and therefore represent new product introductions. I augment this with some descriptive statistics that may support the notion that firms price non-GMO products certified within their product life differently from new products certified before market entry. Then I provide descriptive statistics for consumer demographics to highlight differences between consumers that purchase pre-existing non-GMO products, newly introduced non-GMO products, and non-certified products, which suggests that firms may target new non-GMO product introductions to a specific type of consumers.

1.7.1 Timing of Certification

Figure 1.5 illustrates the number of months a non-GMO product is on the market prior to receiving the Non-GMO Project Verification. A negative value indicates that a product obtained Non-GMO Project Verification prior to appearing in the Nielsen retail scanner data. A significant portion of products in each food category (20% on average) receive certification before entering the market, suggesting that firms may use the label to facilitate new product development and increase product diversity, thereby exercising market power through second-degree price discrimination.

To delve more into Figure 1.5, Table 1.6 presents a comparison of average prices by product category for Non-GMO Project Verified UPCs, based on whether the product already existed in the Nielsen data prior to certification or was newly introduced after certification. "Pre-Existing" products consists of post-certification data for products that are Non-GMO certified and have at least 6 months of sales history prior to certification and 12 months after certification. "New Entry" products consists of the first 3 months of post-certification data for products that are Non-GMO certified and became certified *prior to* appearing in the Nielsen data. The second column shows the percentage of manufacturers in each category for which the mean price of their new entry products exceeded the price of their pre-existing products. The data indicates that, for many product categories, the majority of manufacturers introduced new products at prices greater than those of pre-existing products, further suggesting that firms may use new product entry as a means to extract rent and pass the certification costs for Non-GMO Project Verified products to consumers.

1.7.2 Targeting to Non-GMO Consumers

If firms are potentially developing new non-GMO products and introducing them at higher price points than their existing product line, are these products being targeted to a specific type of consumer? From a future policy standpoint, it is important to understand whether voluntary non-GMO labeling disproportionately affects a particular consumer segment, and whether that impact is beneficial or harmful.[27] To provide some context, I explore how non-GMO consumers differ, on average, from other consumers for the food products in this study.

I use Nielsen Consumer Panel data from 2009 to 2014 for all purchases made in the relevant product categories. Each record represents a household's purchase of a particular product on a specific trip to a store. I calculate mean values for several household demographic variables (income, household size, graduate education, presence of children) across the data, by product non-GMO certification and new entry status (i.e. products certified prior to entering the market, as dicussed in the previous section). The summarized data reflect product- and trip-weighted statistics for household demographics.

Table 1.7 presents results for the consumer demographic analysis. In aggregate, across all 18 food categories, households that consume non-GMO food products tend to be wealthier, smaller, more educated, and less likely to have children. These trends are even more pronounced for consumers of new entry, non-GMO products, further suggesting that firms may target different market segments for new and pre-existing non-GMO products. This evidence, while suggestive, is consistent with the hypothesis that firms strategically introduce new non-GMO certified products to facilitate second-degree price discrimination and pass the non-GMO certification

[27]As a concrete example involving another food policy issue, similar concerns have been raised regarding the soda tax in New York City, which many regard as a regressive tax that is unduly burdensome to households of low socioeconomic status.

cost to consumers.

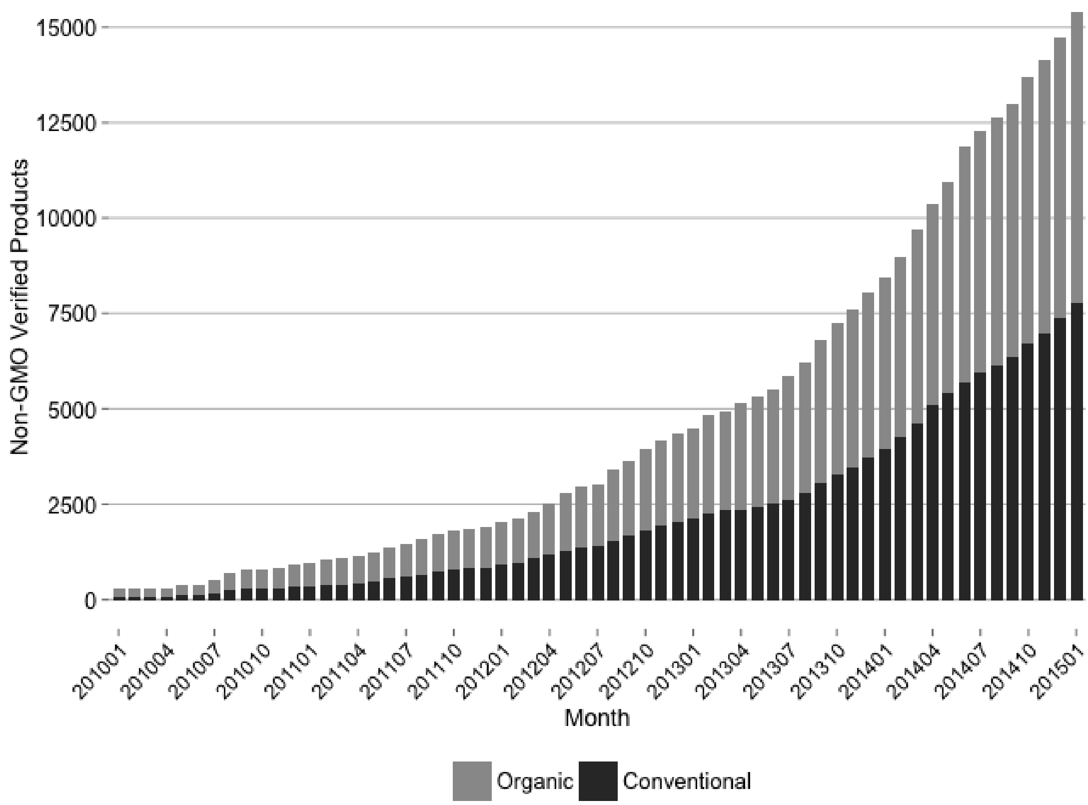
1.8 Conclusion

In recent years, GMO food labeling has become a mainstream debate in the U.S. While the U.S. organic Standard provides an indirect form of non-GMO labeling for Organic food products by prohibiting the use of GMOs, a voluntary verification and labeling scheme for non-GMO products called the Non-GMO Project emerged in the U.S. in 2010. It has grown rapidly to include 35,000 products, accounting for over $13.5 billion in annual sales as of 2015. In this paper, I investigate whether firms use a voluntary, third-party quality certification to exercise market power by extracting price premiums or increasing quantity sold on newly certified products, and whether those effects persist over time. In particular, I use a hedonic framework to estimate price premiums and quantity changes for newly certified non-GMO food products using the Non-GMO Project Verified label in the U.S. I exploit a unique dataset from the Non-GMO Project that contains verification dates for products throughout the label's history, coupled with weekly retail point-of-sale data from 2009 to 2014 for a large sample of supermarkets across the U.S. I find no statistically significant price premiums or quantity changes for newly certified non-GMO food products in the food categories examined. I, however, find suggestive evidence that the label may induce other firm strategies such as new non-GMO product development targeted to specific consumers by which firms could extract rent and pass the certification cost to consumers.

The findings in the paper warrant more in-depth analysis along two fronts. First, while firms do not appear to extract price premiums or increase quantities sold for newly certified non-GMO products that already exist in their product line, some evidence suggests that firms may exercise market power through new non-GMO product introduction. Exploring this type of behavior is best suited to a rigorous structural model that can account for market structure and firm branding strategy. Second, consumers clearly differ in their preferences for non-GMO products, and, therefore, the behavioral effect of the Non-GMO Project Verified certification is not entirely straightforward. Furthermore, if firms behave strategically, perhaps exploiting the non-GMO certification to increase profits through second degree price discrimination, the welfare implications of the certification are also unclear. To quantify these effects, a structural demand model that captures heterogeneity in consumer preferences for non-GMO products is essential.

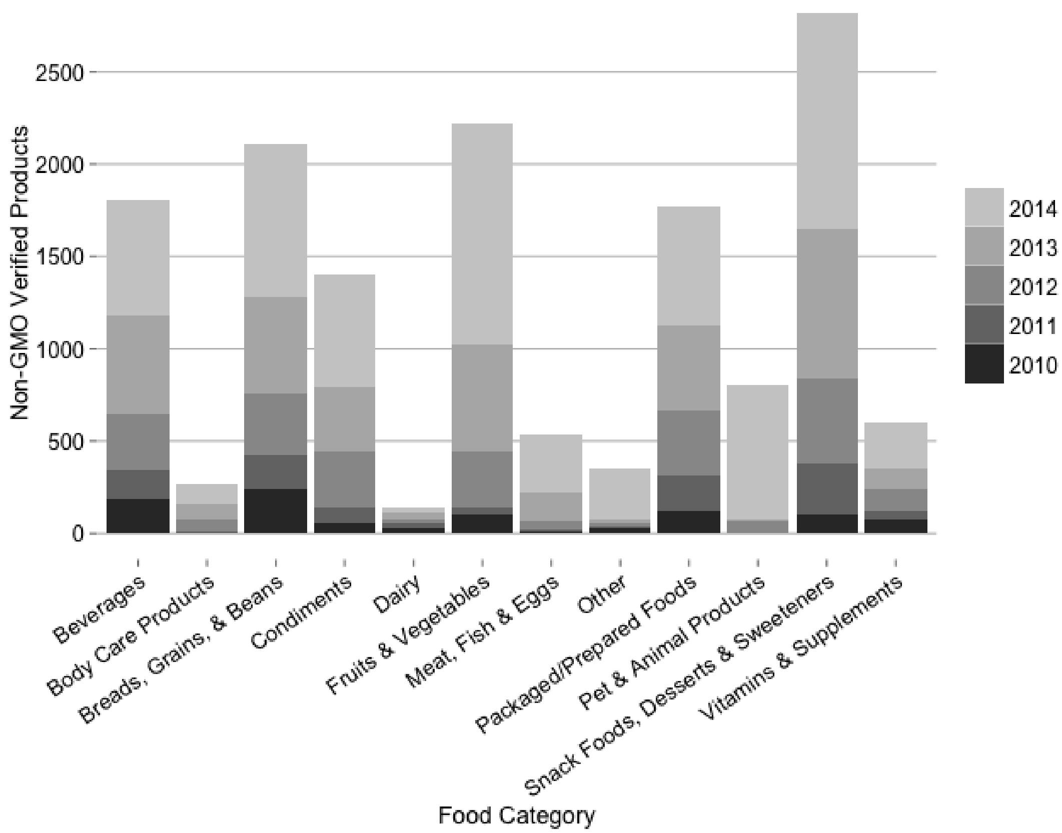
Source: The Non-GMO Project, 2016.

Figure 1.1: Non-GMO Project Verified Label



Note: Product counts are not unique by package specification.

Figure 1.2: Cumulative Monthly Non-GMO Project Verified Products by Organic Status



Note: Product counts are not unique by package specification.

Figure 1.3: Growth in Non-GMO Project Verified Products by Product Category

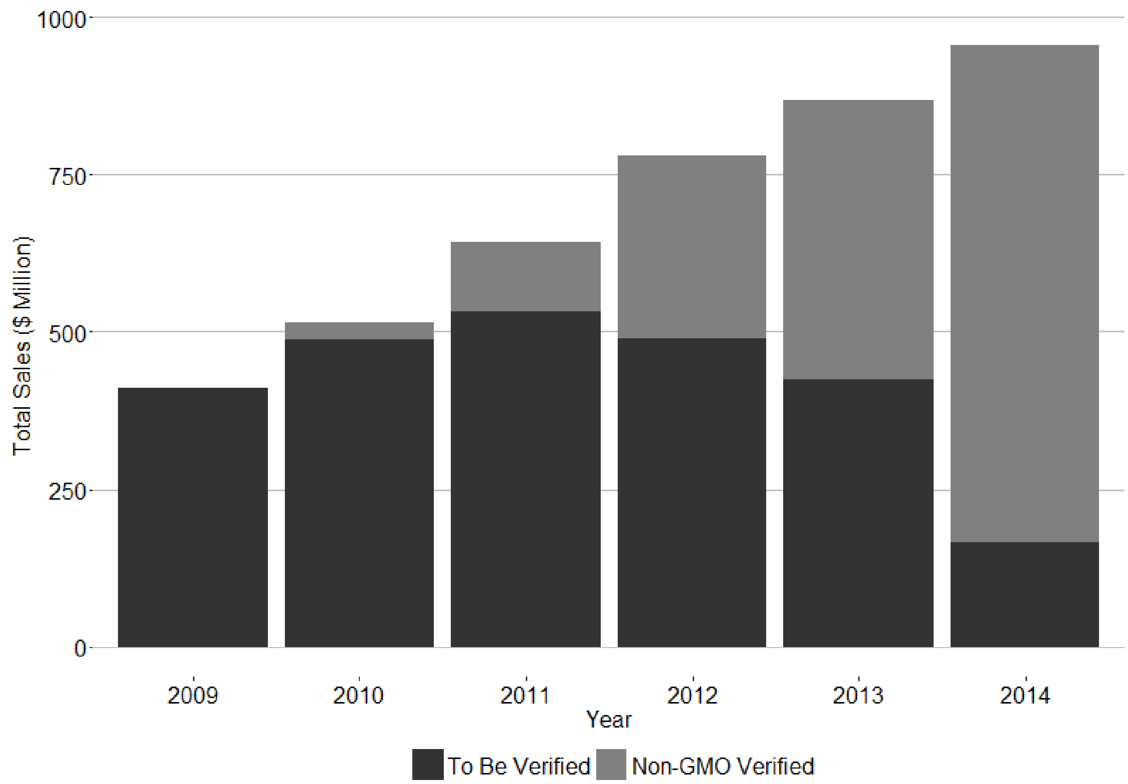
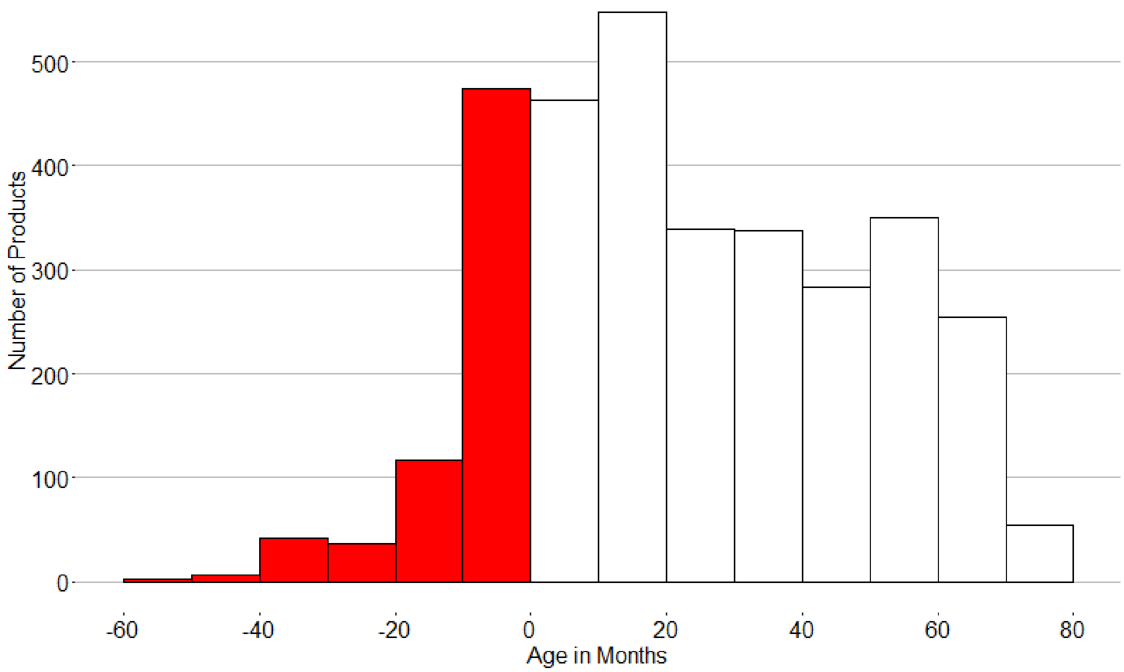


Figure 1.4: Annual Non-GMO Project Verified Product Sales



Note: Product ages are capped at 60 months based on the time span of the data.

Figure 1.5: Product Age When Non-GMO Project Verified

Table 1.1: Summary Statistics

Product Category	Total UPCs	Mfrs.	Organic UPCs	Non-GMO Verified UPCs	Mean Price ($/oz)
BABY FOOD - STRAINED	939	26	442	198	0.19
CANDY-CHOCOLATE	12868	1237	393	153	0.35
NUTS - BAGS	5655	626	86	153	0.44
SNACKS - POTATO CHIPS	5871	252	13	154	0.29
CEREAL - GRANOLA & NATURAL	914	197	106	126	0.24
CEREAL - READY TO EAT	2923	137	186	240	0.20
COOKIES	15886	1655	180	172	0.23
FRUIT-DRIED AND SNACKS	3840	496	320	262	0.34
FRUIT DRINKS-OTHER CONTAINER	6433	815	310	141	0.03
GRANOLA & YOGURT BARS	3264	310	334	229	0.37
OLIVE OIL	1811	487	103	72	0.28
PASTA-SPAGHETTI	1335	289	114	41	0.09
RICE - PACKAGED AND BULK	1418	375	84	151	0.07
SALAD AND COOKING OIL	1062	351	85	90	0.08
SEASONING-DRY	12184	1422	633	410	0.84
SNACKS - TORTILLA CHIPS	2353	346	54	154	0.24
TEA - BAGS	2482	300	379	117	0.09
TEA - HERBAL BAGS	1996	263	340	185	0.17

Table 1.2: Manufacturer-Category Variation in Certification Timing

Product Category	Average Weeks b/t Certification
BABY FOOD - STRAINED	46.51
CANDY-CHOCOLATE	24.87
NUTS - BAGS	9.51
SNACKS - POTATO CHIPS	7.32
CEREAL - GRANOLA & NATURAL	2.13
CEREAL - READY TO EAT	23.48
COOKIES	21.75
FRUIT-DRIED AND SNACKS	14.49
FRUIT DRINKS-OTHER CONTAINER	20.53
GRANOLA & YOGURT BARS	8.70
OLIVE OIL	0.41
PASTA-SPAGHETTI	5.33
RICE - PACKAGED AND BULK	9.56
SALAD AND COOKING OIL	28.38
SEASONING-DRY	32.86
SNACKS - TORTILLA CHIPS	20.55
TEA - BAGS	20.93
TEA - HERBAL BAGS	23.70

Table 1.3: Price Premium Regressions

	I	II	III
Pre-Cert. 6-12 Mos.	-0.010^{**}	-0.012^{*}	-0.010
	(0.003)	(0.006)	(0.007)
Pre-Cert. 0-6 Mos.	-0.013^{**}	-0.007	-0.001
	(0.005)	(0.008)	(0.009)
Post-Cert. 0-6 Mos	-0.033^{***}	$-0.018^{\cdot}$	-0.013
	(0.006)	(0.011)	(0.011)
Post-Cert. 6-12 Mos.	-0.038^{***}	-0.028^{*}	-0.021
	(0.007)	(0.013)	(0.013)
Post-Cert. 12-24 Mos.	-0.045^{***}	-0.022	-0.011
	(0.009)	(0.017)	(0.018)
Post-Cert. 24+ Mos.	-0.062^{***}	-0.036	-0.018
	(0.012)	(0.022)	(0.022)
UPC FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
× Category	Yes	No	Yes
× Manufacturer	No	Yes	Yes
Adj. R^2	0.986	0.989	0.989
Num. obs.	351052	351052	351052

Note: Each column represents a separate regression. Standard errors are clustered at the product level in parentheses: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 1.4: Price Premium Regressions with Organic Interaction

	I	II	III
Pre-Cert. 6-12 Mos.	0.006	−0.003	−0.001
	(0.006)	(0.010)	(0.011)
Pre-Cert. 0-6 Mos.	0.007	−0.002	0.005
	(0.007)	(0.012)	(0.012)
Post-Cert. 0-6 Mos	−0.013	−0.009	−0.004
	(0.008)	(0.014)	(0.015)
Post-Cert. 6-12 Mos.	−0.027**	−0.015	−0.008
	(0.009)	(0.016)	(0.017)
Post-Cert. 12-24 Mos.	−0.034**	0.003	0.014
	(0.011)	(0.020)	(0.022)
Post-Cert. 24+ Mos.	−0.053***	−0.024	−0.010
	(0.014)	(0.024)	(0.025)
Pre-Cert. 6-12 Mos. × Organic	−0.028***	−0.018	−0.017
	(0.008)	(0.011)	(0.012)
Pre-Cert. 0-6 Mos. × Organic	−0.035***	−0.008	−0.010
	(0.009)	(0.011)	(0.012)
Post-Cert. 0-6 Mos × Organic	−0.035***	−0.016	−0.016
	(0.009)	(0.012)	(0.012)
Post-Cert. 6-12 Mos. × Organic	−0.019·	−0.022·	−0.021
	(0.010)	(0.013)	(0.013)
Post-Cert. 12-24 Mos. × Organic	−0.019·	−0.042**	−0.043**
	(0.010)	(0.013)	(0.014)
Post-Cert. 24+ Mos. × Organic	−0.015	−0.017	−0.013
	(0.011)	(0.013)	(0.014)
UPC FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
× Category	Yes	No	Yes
× Manufacturer	No	Yes	Yes
Adj. R^2	0.986	0.989	0.989
Num. obs.	351052	351052	351052

Note: Each column represents a separate regression. Standard errors are clustered at the product level in parentheses: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 1.5: Quantity Regressions

	I	II	III
Pre-Cert. 6-12 Mos.	0.044	−0.020	−0.048
	(0.037)	(0.054)	(0.056)
Pre-Cert. 0-6 Mos.	0.062	−0.011	−0.040
	(0.049)	(0.077)	(0.078)
Post-Cert. 0-6 Mos	0.138^{*}	0.060	0.027
	(0.062)	(0.098)	(0.097)
Post-Cert. 6-12 Mos.	$0.144^{\cdot}$	0.151	0.120
	(0.077)	(0.123)	(0.119)
Post-Cert. 12-24 Mos.	0.116	0.218	0.187
	(0.103)	(0.164)	(0.160)
Post-Cert. 24+ Mos.	0.164	0.300	0.277
	(0.143)	(0.224)	(0.211)
UPC FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
× Category	Yes	No	Yes
× Manufacturer	No	Yes	Yes
Adj. R^2	0.858	0.901	0.903
Num. obs.	351052	351052	351052

Note: Each column represents a separate regression. Standard errors are clustered at the product level in parentheses: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 1.6: Non-GMO Certification of New and Pre-Existing Food Products

Product Category	Pct. Mfrs. New Entry > Pre-Existing Mean Price (%)	New Entry UPCs	Pre-Existing UPCs
BABY FOOD - STRAINED	100.0	57	81
CANDY-CHOCOLATE	25.0	46	67
NUTS - BAGS	80.0	30	85
SNACKS - POTATO CHIPS	66.7	31	83
CEREAL - GRANOLA & NATURAL	100.0	42	56
CEREAL - READY TO EAT	70	68	121
COOKIES	55.6	59	91
FRUIT-DRIED AND SNACKS	44.4	65	87
FRUIT DRINKS-OTHER CONTAINER	60.0	38	80
GRANOLA & YOGURT BARS	33.3	55	87
OLIVE OIL	50.0	12	24
PASTA-SPAGHETTI	0.0	14	19
RICE - PACKAGED AND BULK	75.0	52	73
SALAD AND COOKING OIL	60.0	25	52
SEASONING-DRY	33.3	26	228
SNACKS - TORTILLA CHIPS	50.0	25	84
TEA - BAGS	100.0	22	75
TEA - HERBAL BAGS	62.5	33	96

Table 1.7: Average Consumer for Conventional & Non-GMO Products

Non-GMO	Product	Mean Inc.	Median Inc.	HH Size	Grad Edu.	Child
No	All	$65607	[$50K, $60K)	2.70	0.16	0.30
Yes	Pre-Existing	$68508	[$50K, $60K)	2.60	0.20	0.28
Yes	New	$77277	[$60K, $70K)	2.53	0.25	0.26

Chapter 2: The Impact of Voluntary Non-GMO Labeling on Demand in the Ready-to-Eat Cereal Industry*

2.1 Introduction

In markets with asymmetric information, quality disclosure can lead to efficiency gains that benefit consumers and producers (Grossman 1981; Dranove and Jin 2010). Firms may also use quality certification to influence perceived product quality and exercise market power. This paper examines the impact of voluntary quality certification on demand in the ready-to-eat [RTE] cereal industry, using evidence from the Non-GMO Project Verified food label. While past studies have investigated firms' use of non-price marketing strategies such as advertising, couponing, and new product introductions in the RTE cereal industry (Thomas 1999; Nevo 2001; Nevo and Wolfram 2002), this paper is the first to examine the role of voluntary quality certification as a marketing strategy in this industry.

Prior hedonic analysis does not find evidence of price premiums or quantity changes for newly certified non-GMO food products across 18 food categories, including RTE cereal (Adalja 2016). In this study, I estimate a discrete-choice, random

*Nielsen data is provided by the Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen.

coefficients logit demand model (Berry et al. 1995; Nevo 2001) with monthly Nielsen Retail Scanner data for 50 breakfast cereal brands in 100 DMAs between 2010 and 2014. I use the model to examine the impact of voluntary non-GMO labeling on demand for RTE cereal and to characterize heterogeneity in consumer tastes for non-GMO labeling. The results indicate that consumer preferences vary significantly for the non-GMO label, and this heterogeneity affects individual choices. In aggregate, the non-GMO label positively impacts demand on average.

I use the structural parameters recovered from the demand estimation along with an assumed model of firm behavior to calculate price-cost margins. I use these results to simulate welfare effects for two different labeling regimes in the RTE cereal industry: one in which all brands use the non-GMO label and one in which no brands use the label. I analyze changes in producer and consumer welfare by analyzing changes in firm profit and individual compensating variation, respectively. The simulation results suggest that non-GMO labeling in the RTE cereal industry may improve consumer surplus but reduce industry profit on average.

Several factors make the RTE cereal food category well suited for estimating the effects of voluntary non-GMO food labeling on demand. First, there exists substantial variation in non-GMO labeling across time and products in this category. Second, the data that I use have an exhaustive coverage of the purchases for these products. Finally, RTE cereal has a long history of study in empirical industrial organization, so parameter estimates are readily available in the literature with which to benchmark my model estimates.

The paper is structured as follows. Section 2.2 discusses the literature on the RTE cereal industry, willingness to pay for non-GMO, and demand estimation. Section 2.3 presents the theoretical framework for the structural economic model and welfare analysis. Section 2.4 describes the data sources I employ to implement this study. Section 2.5 highlights the empirical strategy I use to estimate the demand system. Section 2.6 presents parameter estimates recovered from the model and the simulated welfare effects of non-GMO labeling. Lastly, Section 2.7 offers concluding remarks as well as opportunities for future extensions to the analysis.

2.2 Background Literature

2.2.1 Demand Estimation in Markets with Differentiated Products

Demand estimation has a long history in economics research dating back to Stone (1954), but estimating structural demand models for differentiated products has historically posed several obstacles. First, due to the large number of products, simply estimating a system of demand equations is empirically intractable due to the large number of parameters to estimate. Another problem that must be addressed is consumer preference heterogeneity, of which the proliferation of differentiated products is a manifestation. Discrete choice models such as the logit demand model (McFadden 1973) circumvent the dimensionality issue by transforming each product into a bundle of relevant attributes, thereby shrinking the dimensions of the system. However, due to the model assumptions, the standard logit model carries with it strong restrictions on consumer substitution patterns.

Of the many advances that have occurred since then, the methodology developed in Berry (1994) and Berry et al. (1995) [BLP] represents a significant innovation for demand estimation in differentiated-products markets. In this seminal work, BLP estimates a random-coefficients discrete choice demand model by using a fixed-point contraction mapping to solve the system numerically. The BLP model incorporates preference heterogeneity and allows for more flexible substitution patterns, but these features come at the expense of significant computational complexity. Thanks in part to Nevo (2000b), who made MATLAB code for BLP estimation publicly available, the BLP model has seen wide use in empirical industrial organization, underlying much of the work in demand estimation conducted over the past two decades.

Since then, several additional improvements have been made within this estimation framework. Nevo (2001) extended this model by incorporating panel data techniques such as brand fixed effects and partially relaxing parametric assumptions for preference heterogeneity by drawing from an empirical distribution of consumers. Petrin (2002) uses average consumer data relating demographics to purchase probability to fit additional moment restrictions, thus obtaining more precise estimates of structural parameters. Berry et al. (2004) uses detailed consumer-level data on consumers' second choices to fit three sets of moments, thus providing an alternative source of identification. Despite its widespread use, the BLP estimation technique presents significant numerical challenges. Dubé et al. (2012) and Knittel and Metaxoglou (2014) both conduct comprehensive analyses of the algorithms used to estimate random-coefficients logit demand models and show that results vary widely depending on the algorithm, starting values, and tolerances. As such, it is critical that researchers exercise extreme caution when estimating these types of models.

2.2.2 Ready-to-Eat Cereal Industry

There has been sustained interest among economists in the RTE cereal industry since the 1970s, when the FTC brought an antitrust suit against Kellogg, General Mills, and Post. The industry exhibits some of the classic traits of a differentiated oligopoly—high concentration, enormous brand proliferation, and frequent new product introductions. The early literature on the RTE cereal industry directly addresses the antitrust concerns raised by the FTC. Schmalensee (1978) use's the Hotelling model to analyze firm conduct in the RTE cereal industry and argues that frequent new product introductions by incumbent firms serve to protect profits and deter new entry in the industry.[2] Scherer (1979) looks at new product introductions as well, but from a welfare perspective. He provides evidence suggesting that product variety is overstimulated and, based on launching costs, very likely welfare reducing at the margin.

More recent literature on the RTE cereal industry tends to focus on either price or non-price marketing strategies. Thomas (1999) examines firm response to entry and finds that incumbent response depends on the scale of entry, and firms use advertising and new product introductions for entry deterrence in addition to price. Nevo (2001) uses a BLP approach to measure market power in the RTE cereal industry. He finds that the high price-cost margins in the industry are largely explained

[2]This paper is based upon the author's expert testimony as a government witness in the aforementioned FTC antitrust case.

by product differentiation and multi-product firm pricing rather than collusive behavior, suggesting that any market power is attributable a firm's product portfolio and advertising. Nevo (2000a) uses the same model to analyze the effects of mergers in the industry by using the structural parameters recovered from BLP estimation to simulate new price equilibria and welfare changes of various merger scenarios (two of which actually occurred). Nevo and Wolfram (2002) analyze the relationship between shelf prices and coupons in the RTE cereal industry. Interestingly, they find a negative correlation between prices and availability of manufacturer coupons. They present evidence that this behavior is driven by strategic interaction between firms, manager incentives, and the effects of coupons on repeat purchase.

In an effort to address both price and non-price strategies, Richards and Patterson (2006) uses a dynamic setting to examine strategic interaction between firms. They find that firms tend to price and choose product lines cooperatively in the static setting; but, with dynamic interactions, firms behave more competitively along both dimensions. Chidmi (2012) examines vertical relationship between retailers and manufacturers in the RTE cereal industry to shed light on retail pricing decisions. He estimates different supply models using demand parameters recovered from BLP estimation with data from four supermarket chains in the Boston area. The results imply that manufacturers make pricing decisions and retailers do not intervene (i.e. retailer margins are zero), thus avoiding double-marginalization. Richards and Hamilton (2015) examines pass-through of wholesale price changes into retail prices and product lines of firms in the RTE cereal industry. By accounting for the endogeneity of product line decisions for multi-product firms, they find evidence that wholesale price changes are passed through one-to-one to retail prices.

2.2.3 Willingness-to-Pay for Non-GMO

Empirical studies of willingness-to-pay [WTP] for non-GMO labeling have decidedly mixed findings. Most studies employ surveys and lab experiments to analyze consumer preferences for GMO products. Lusk et al. (2005) identifies 25 separate studies that together provide 57 estimates of consumers' WTP for GMO food products and finds significant variation in the estimates. Price premiums for non-GMO food ranged from -68% to 784%, with an average of 42%, and are significantly affected by elicitation method.

Recent studies attempt to shed light on the source of this variation. Using data from a nationwide survey, Onyango et al. (2006) finds that consumers place a 10% premium on food labeled as non-GMO and 6.5% discount on food labeled as GMO; but, interestingly, consumers also attach a 5% premium for food labeled GMO if the label also specifies "USDA approved" or "to reduce pesticide residues in your food." Roe and Teisl (2007) uses a survey to elicit consumer reactions to 80 different GMO label variations and finds that labels with simple claims and claims certified by the FDA are most credible. Costanigro and Lusk (2014) conducts a series of choice experiments and finds evidence that consumer WTP to avoid GMO food is 140% higher with a mandatory "contains" GMO label compared to a voluntary "does not contain" GMO label. Lastly, Adalja (2016) uses national retail scanner data for 18 food categories coupled with labeling data from the Non-GMO

Project Verified voluntary label and finds no evidence of price premiums for non-GMO products; however, suggestive evidence supports the hypothesis that the label induces incumbent firms to introduce new products.

2.3 Conceptual Framework

The conceptual approach as well as the empirical strategy for the structural model follows very closely with the framework of Nevo (2001), so I present an abbreviated treatment here using the same notation.

2.3.1 Consumer Demand with Heterogeneous Preferences

Consider an economy in which we observe $t = 1, \ldots, T$ markets, each with $i = 1, \ldots, I_t$ consumers and $j = 1, \ldots, J$ products with average prices p_{jt}. The indirect utility of consumer i from consuming product j in market t is

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{2.1}$$

where x_{jt} is a K-dimensional vector of observable product characteristics, ξ_{jt} is the unobserved product characteristic, (β_i, α_i) are $K+1$ individual-specific coefficients, and ε_{ijt} is a mean-zero stochastic term. The unobserved product characteristic ξ_{jt} can be further decomposed as $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$, where ξ_j and ξ_t can be captured empirically with brand and time dummies, respectively, in which case x_{jt} only contains time-varying product characteristics. The indirect utility from the outside option is normalized to zero.

Consumer preferences depend on individual demographics D and unobserved individual characteristics v, which are formally modeled as a

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \quad v_i \sim P_v(v), \quad D_i \sim P_D(D), \tag{2.2}$$

where D_i is a $d \times 1$ vector of demographics that follow the distribution P_D, v_i is a $K+1$ vector of mean-zero normally distributed unobservables that follow the distribution P_v, Π is a $(K+1) \times d$ matrix of coefficients that measure how tastes (for observable characteristics) vary with demographics, and Σ is a $(K+1) \times (K+1)$ matrix of parameters. If we observe individual demand data, we can use such data to characterize D_i nonparametrically by drawing from an empirical distribution $\hat{P}_D$ such as the Current Population Survey [CPS] or the Nielsen Consumer Panel.

The set of individual characteristics that lead to product choice j are implicitly defined by

$$A_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \{(D_i, v_i, \varepsilon_{it}) | u_{ijt} \geq u_{ilt}\}, \ \forall\, l = 1, \ldots, J.$$

If we assume that D, v, and ε are independent, the market share for product j is the integral

$$s_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP(D, v, \varepsilon) = \int_{A_{jt}} dP_\varepsilon(\varepsilon) dP_v(v) dP_D(D), \tag{2.3}$$

which can be computed either analytically or numerically depending on the distributional assumptions made on D, v, and ε.

2.3.2 Firm Behavior

Assume there are $f = 1, \dots, F$ firms, and each firm produces a subset $\mathfrak{F}_f$ of the J products. Profit is calculated as

$$\Pi_f = \sum_{j \in \mathfrak{F}_f} (p_j - mc_j) M s_j(p) - C_f,$$

where $s_j(p)$ is the market share of product j, M is the market size, and C_f is the fixed cost. Assuming a Bertrand-Nash equilibrium in prices, the first order condition with respect to price for each product j is

$$s_j(p) + \sum_{r \in \mathfrak{F}_r} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0.$$

We can construct the $J \times J$ price derivative matrix S where each element $S_{jr} = -\frac{\partial s_r(p)}{\partial p_j}$ and the $J \times J$ ownership matrix Ω^o where each element $\Omega_{jr} = 1$ if products r and j are owned by the same firm or zero otherwise. If I define the matrix Ω as the Hadamard product of Ω^o and S and express for s, p, and mc as $J \times 1$ vectors, I can solve for the price-cost margins as

$$p - mc = \Omega^{-1} s(p). \tag{2.4}$$

Once demand parameters are recovered, Equation 2.4 can be used estimate marginal costs for each brand.

2.4 Data

Estimating a demand system for differentiated products requires, at a minimum, marketing data with prices, market share, and product characteristics across several markets in the U.S. These data typically consist of consumer panel data, aggregate market-level data, or both. Models that use individual data account for consumer heterogeneity and allow for a high level of product differentiation. They also circumvent price endogeneity issues common to aggregate demand models (e.g., Goldberg 1995). That said, an aggregate industry model explicitly addresses supply side and equilibrium considerations. Ideally, an estimation strategy that combines both approaches can enrich the analysis by addressing demand, supply, and market equilibrium together (e.g., Nevo 2001; Petrin 2002; Berry et al. 2004).

I use month-DMA-brand-level data between 2010 and 2014 (each market is a DMA-month, for a total of 5,988 markets) on prices, market shares, and brand characteristics from the Nielsen Retail Scanner Data; and I combine it with non-GMO labeling data from the Non-GMO Project. Additionally, to complete the demand system, I must specify the market share for the outside good in each market, which requires an estimate of overall market size. I use data from the U.S. Census Bureau's Annual Estimates of the Resident Population for Counties along with household sales data for RTE cereal from the Nielsen Consumer Panel to construct this estimate. Lastly, I draw consumer demographics from the CPS Annual Supplement.

2.4.1 Nielsen Retail Scanner and Consumer Panel Data

The Nielsen Retail Scanner data contains weekly, UPC-level quantity and price data from retail store point-of-sale systems for 35,000 retail stores covering more than half the total sales volume of grocery stores across the U.S. The full dataset contains 2.6 million UPCs, representing 1,100 Nielsen product categories. RTE cereal represent one such product category. I aggregate the RTE cereal data by month, DMA, and brand (e.g., General Mills Honey Nut Cheerios is one brand, etc.). Volume sales data is standardized by converting quantity to ounces sold, and market share is calculated by dividing ounces sold by potential market size (see Section 2.4.3 for details on the derivation of market size). A standardized price variable is calculated as total dollar sales divided by ounces sold, and real prices are adjusted using the U.S. average monthly urban CPI for breakfast cereal.

If one was simply interested in estimating demand for the major brands in the RTE cereal industry, an appropriate way to choose brands would be to select the J brands with the top national market share. However, since I am primarily interested in examining how a voluntary non-GMO label affects demand for RTE cereal, it is critical that the brands chosen accurately reflect the market for non-GMO RTE cereal. Accordingly, the brands used in the demand estimation must include those which started using the non-GMO label between 2010 and 2014 and unlabeled brands that may be considered viable substitutes for these products.

I use information from Nielsen Consumer Panel to select brands to use in the demand estimation. The Nielsen Consumer Panel data contains trip-UPC-level purchase and pricing data for a nationally-representative panel of 40,000 to 60,000 U.S. households, covering the same product categories as the Retail Scanner data for all major retail channels. To determine the relevant brands, I first identify households that purchased newly launched Non-GMO Project Verified RTE cereal brands in 2014.[3] I then examine the portfolio of RTE cereal brands previously purchased by these same households, and I choose the top 50 brands based on projected volume purchased between 2010 and 2014. I then restrict the total number of markets in my final dataset by selecting the 100 DMAs with the highest total volume of sales for these 50 brands. Table 2.1 presents summary statistics by brand for the variables used in the estimation.

2.4.2 Non-GMO Project

To estimate the effect of a non-GMO food label on demand for RTE cereal, I have secured a unique, UPC-level monthly dataset of non-GMO products from the Non-GMO Project[4] that identifies the date each product began using the Non-GMO Project Verified label. The Non-GMO Project began offering third-party verification and labeling for food products in 2010, and the dataset spans 2010 to 2014. Usage of the label has grown rapidly since 2010; the Non-GMO Project currently verifies

[3]These are brands that entered the market between 2010 and 2014 with Non-GMO Project Verification already in place *prior to* appearing in the Nielsen data.

[4]See Adalja (2016) for a comprehensive background on the Non-GMO Project.

over 3,000 brands that represent more than 43,000 products and $19.2 billion in sales (Non-GMO Project 2017). Figure 2.1 shows total national sales for Non-GMO Project Verified RTE cereal products between 2010 and 2014, based on the Nielsen Retail Scanner data. To help distinguish between growth from newly introduced products and existing products, the figure also show sales for products verified in a future calendar year, denoted "To Be Verified." I merge this data by UPC with Nielsen Retail Scanner data to clearly identify the month in which RTE cereals began using the Non-GMO Project Verified label.

2.4.3 Market Size

We do not directly observe the market share for the outside good—it is calculated as the total market size less the market share of the inside goods. We must, therefore, define the total market size. This is generally done by choosing an observable variable to which market size is proportional as well as a proportionality factor to calculate actual market size (Nevo 2000b). In the case of the RTE cereal industry, we ultimately need a measure of the monthly market size, in terms of quantity of RTE cereal consumed, for each DMA in the sample. I assume the market size in each DMA-month is proportional to the population size. I construct monthly estimates of the population size for each DMA between 2010 and 2014 using the U.S. Census Bureau's Annual Estimates of the Resident Population for Counties. I assume the population is constant across all months in a given year. DMAs consist of non-overlapping counties, so aggregating these population estimates to the

DMA-level is straightforward.

To estimate the proportionality factor, I use the national, trip-level Nielsen Consumer Panel data from 2010 to 2014 to calculate the total volume (in ounces) of RTE cereal consumed per household, per year. I then use each household's size to calculate the total number of individuals in the sample and construct a yearly measure of average daily per capita consumption. On average, daily per capita cereal consumption between 2010 and 2014 is about 0.5 ounces (about half a serving per person per day for a typical breakfast cereal); however, it declines slightly each year over this time period, suggesting that the RTE cereal market is shrinking. To accurately capture the changing market size, I let the daily per capital consumption estimate vary by year. Multiplying by the number of days in each month, I construct the final proportionality factor to use with monthly population estimates above to define market size: average monthly per capita RTE cereal consumption in ounces. I use market size along with the quantity data from the Nielsen Retail Scanner data to calculate brand market shares to use in demand estimation.

2.4.4 Consumer Demographic Data

To construct an empirical distribution of consumer demographics, I use data from the Annual Social and Economic Supplement to the Current Population Survey for 2010 through 2014. Using county information and the sample weights provided in the survey, I sample 50 individuals for each DMA each year (the data is the same across all months in a given year). The variables include age, household income, and household size. I calculate individual income as household income divided by household size, and I also define a child indicator variable that equals one if $age < 16$. The final demographic variables used in the estimation are logarithm of income, logarithm of income-squared, age, and child. For stability in the estimation procedure, log income and age are demeaned and scaled by their standard deviations; and log income-squared and child are demeaned. Table 2.2 contains summary statistics by DMA for the demographic variables used in estimation.

2.5 Empirical Approach

2.5.1 Demand Estimation

By defining $\theta = (\theta_1, \theta_2)$ as a vector of all the parameters in the structural demand model, where $\theta_1 = (\alpha, \beta)$ are the linear parameters and $\theta_2 = (\Pi, \Sigma)$ are the nonlinear parameters, we can combine Equations 2.1 and 2.2 to express utility as

$$u_{ijt} = \delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) + \varepsilon_{ijt}, \tag{2.5}$$

$$\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_j + \xi_t + \Delta\xi_{jt}, \quad \mu_{ijt} = [-p_{jt}, x_{jt}]' * (\Pi D_i + \Sigma v_i).$$

In this formulation, δ_{jt} contains only linear parameters and is devoid of any individual-specific parameters, so it represents the mean utility common to all consumers. The terms $\mu_{ijt} + \varepsilon_{ijt}$ represent a mean-zero deviation from the mean, capturing the individual random coefficients. Consumer tastes are distributed as multivariate normal, conditional on demographics, such that $v_i \sim N(0, I_{K+1})$. The vector of demographics D is sampled from the CPS and includes variables for log income, log income-squared, age, and a child indicator. Because I include brand-specific dummy variables (ξ_j), x_{jt} only contains a time-varying indicator for non-GMO certification that equals one when a product receives Non-GMO Project Verification and zero otherwise.

We assume the ε_{ijt} is distributed i.i.d. according to a Type I extreme value distribution, but allow for correlation between choices through the term μ_{ijt}. Under these assumptions, I calculate individual purchase probabilities as

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{K} \exp(\delta_{kt} + \mu_{ikt})} \tag{2.6}$$

and product market shares as

$$s_{jt} = \frac{\sum_{i=1}^{I_t} s_{ijt}}{I_t}. \tag{2.7}$$

To address correlation between prices p and the structural error term $\Delta\xi_{jt}$, we introduce a set of price instruments $Z = [z_1, \ldots, z_M]$ and use the estimation method developed by Berry (1994) to construct a nonlinear GMM estimator based on the moment condition:

$$E[Z_m \, \omega(\theta^*)] = 0, \quad m = 1, \ldots, M,$$

where ω is the structural error term (see below) and θ^* are the true parameter values. The estimation routine entails minimizing the GMM objective function to calculate an estimate of θ^* such that

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\ \omega(\theta)' Z A^{-1} Z' \omega(\theta) \tag{2.8}$$

where A is an appropriate weight matrix—i.e., a consistent estimate of $E[Z'\omega\omega' Z]$. To express the structural error term as a function of the parameters, we must first calculate the vector of mean utilities $\delta_{\cdot t}$ for each market t. To do so, we equate the calculated market shares from Equation 2.7 with observed market shares from the data:

$$s(\delta_{\cdot t}; \theta_2) = S_{\cdot t} \tag{2.9}$$

and solve for $\delta_{\cdot t}$ by inverting the system of market share equations numerically using the BLP contraction mapping:

$$\delta_{\cdot t}^{(k+1)} = \delta_{\cdot t}^{(k)} + \ln S_{\cdot t} - \ln s(\delta_{\cdot t}^{(k)}; \theta_2), \tag{2.10}$$

where k denotes the fixed-point iteration. Once δ is computed, the error term can be calculated as

$$\omega_{jt} = \delta_{jt}(S_{\cdot t}; \theta_2) - x_{jt}\beta - \alpha p_{jt} \tag{2.11}$$

and used directly in Equation 2.8. The elements of θ_1 in Equation 2.11 are obtained using linear instrumental variables regression. Nevo (2000b) and Nevo (2001) provide additional details on the estimation strategy, and Appendix B.2 documents several improvements and deviations in my own computational strategy.

Once I have estimated the structural demand parameters, I can calculate the partial derivatives of market shares with respect to prices as

$$\frac{\partial s_j(p)}{\partial p_k} = \begin{cases} \frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}(1-s_{ijt}) & \text{if } j=k, \\ -\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt} s_{ikt} & \text{otherwise.} \end{cases} \tag{2.12}$$

I calculate the price elasticities of the market shares s_{jt} as

$$\eta_{jkt} = \begin{cases} \frac{p_{jt}}{s_{jt}}\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}(1-s_{ijt}) & \text{if } j=k, \\ -\frac{p_{kt}}{s_{jt}}\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt} s_{ikt} & \text{otherwise.} \end{cases} \tag{2.13}$$

These values are used to calculate price-cost margins and to simulate welfare effects.

2.5.2 Price Instruments

While brand and time fixed effects eliminate the unobserved brand-specific and month-specific deviations from the structural error term in Equation 2.5, the DMA-specific component $\Delta\xi_{jt}$ remains. If firms account for this deviation, then DMA-specific valuations will be correlated with the error term, creating a price endogeneity problem and biasing estimates of α. To correct this problem, I use a similar approach to Nevo (2001) to construct price instruments by exploiting the panel structure of the data. The identifying assumption is that DMA-specific valuations are independent across DMAs after controlling for brand, month, and consumer demographics, but prices across DMAs are correlated due to common marginal costs. Under this assumption, for a given DMA, prices of brand j in all other DMAs and across all months are valid instruments. I implement this strategy for each brand j in DMA-month t by constructing monthly average prices for all directly neighboring DMAs and using prices for the twelve nearest months (including the current month) as instruments.

2.5.3 Time-Invariant Product Characteristics

By employing brand fixed effects, taste coefficients for time-invariant product characteristics that may be of interest cannot be recovered directly from the main estimation. For example, organic certification may be seen as a substitute for non-GMO certification, but due to its time-invariant nature in the data sample, its direct effect cannot be estimated. Other time-invariant characteristics of interest include: organic certification interacted with final non-GMO status, new product indicator,[5] kids' cereal indicator, and sugar content. To recover estimated coefficients for these variables, I regress the brand fixed effects recovered from the main estimation on these characteristics using the minimum-distance procedure of Chamberlain (1982). The estimation procedure consists of a GLS regression where the estimated covariance matrix from the main estimation is used as a weight matrix to adjust for correlation in the dependent variable. These results are presented alongside the full model results in Section 2.6.2.

[5] In essence, did the product launch during the time period of the sample or did it exist prior to that?

2.5.4 Welfare Analysis

From a policy standpoint, measuring changes in consumer welfare is a critical component in evaluating different labeling schemes. Using the structural parameters recovered from demand estimation, I simulate the effects of two counterfactual scenarios on consumer welfare. In the first scenario, I assume that the government completely bans the use of GMO ingredients in food and thus requires all 50 brands to undergo non-GMO certification and use the label across all markets in the sample. In the second scenario, I assume the government outlaws non-GMO labeling on food products and thus bans any brands from using the label across all markets in the sample. These scenarios are not entirely unreasonable and warrant consideration. For example, many countries in Europe currently place heavy restrictions on the use of GMO ingredients in food products in what amounts to a ban. As such, most food products undergo non-GMO certification and very few contain GMOs.[6] Additionally, in the U.S., the FDA asserts that approved GMO food products are not significantly different from or less safe than their non-GMO produced counterparts and, thus, do not require additional labeling. Based on that, industry groups have spent years lobbying Congress to pass a law banning any form GMO labeling on the grounds that it would mislead consumers.[7]

In a perfect information environment, one can estimate the changes to con-

[6]At the very least, in many European countries if a food product contains GMOs, it must be clearly labeled as such, creating a stigma that food manufacturers try to avoid.

[7]This effort ultimately lead to the passage of the National Bioengineered Food Disclosure Standard in 2016, which tasks USDA with establishing a national voluntary non-GMO labeling standard.

sumer welfare using a simple measure of compensating variation based on the traditional random utility model. We can calculate the compensating variation for each individual in a given market t as

$$CV_i^P = \frac{1}{\alpha_i}\left[\ln\sum_{j=0}^{J}\exp(\tilde{V}_{ij}) - \ln\sum_{j=0}^{J}\exp(V_{ij})\right], \tag{2.14}$$

where $V_{ij} = \delta_j + \mu_{ij}$ and the terms with a tilde are evaluated after the policy change. Taking the average of this result across all I_t individuals yields the average compensating variation for market t. However, non-GMO food products are credence goods, differentiated by a vertical process attribute unobservable to the consumer, even after consumption (Adalja 2016). Accordingly, in the presence of imperfect information, the traditional multinomial logit measure for compensating variation is biased due to the discrepancy between consumers' decision utility and experience utility (Houde 2016). When the utility function for consumers' purchase decisions does not coincide with the utility function for consumers' post-purchase experiences, the change in consumer surplus for each individual in a given market t can be expressed as

$$\begin{aligned} CV_i^I = {} & \frac{1}{\alpha_i}\left[\ln\sum_{j=0}^{J}\exp(\tilde{V}_{ij}) + \sum_{j=0}^{J}\tilde{s}_{ij}(\tilde{V}_{ij}^E - \tilde{V}_{ij})\right] - \\ & \frac{1}{\alpha_i}\left[\ln\sum_{j=0}^{J}\exp(V_{ij}) + \sum_{j=0}^{J}s_{ij}(V_{ij}^E - V_{ij})\right], \end{aligned} \tag{2.15}$$

where the terms with a tilde are evaluated after the policy change, V_{ij}^E denotes experience utility, and V_{ij} denotes decision utility. The expression in Equation 2.15

differs from the perfect information welfare measure in Equation 2.14 due to the two correction terms of the form $\sum_{j=0}^{J} s_{ij}(V_{ij}^{E} - V_{ij})$. These terms account for the discrepancy between consumers' perceptions that guide decision making and what they actually experience (see Leggett 2002, for a full derivation). Note that if no discrepancy exists between the two utility functions, then the expression in 2.15 reduces to the perfect information welfare measure in 2.14.

Given the credence good nature of the non-GMO product attribute, one might argue that a non-GMO label affects decision utility, but it does not impact experience utility due to the fact that the attribute cannot be physically experienced, even after consumption. Such an argument suggests the use of Equation 2.15 for calculating welfare effects of a policy change. The possibility also exists that consumers who purchase non-GMO products experience a warm glow (Andreoni 1990), or the certification may affect social status in some way, such that the label also impacts experience utility, despite the fact that it cannot be physically sensed. If the non-GMO label's impact on decision and experience utility are aligned, then Equation 2.14 is an appropriate measure for welfare analysis. Given these competing arguments, I present welfare estimates using both expressions for changes in consumer surplus in the results.

2.6 Results

2.6.1 Logit Specification

In Equation 2.5, if we assume that consumer heterogeneity only enters the model through the error term ε_{ijt} (such that $\theta_2 = 0$, $\beta_i = \beta$, and $\alpha_i = \alpha$ for all consumers), and we assume that ε_{ijt} is distributed as i.i.d. Type I extreme value; then the model distills to a logit specification. In this case, Equation 2.9 can be solved analytically as $\delta_{jt} = \ln(S_{jt}) - \ln(S_{0t})$, where S_{0t} is the observed outside market share for market t, and the estimation procedure simplifies to 2SLS. The logit specification places strong restrictions on the model—it implies that cross-price elasticities are only a function of market share; however, it can serve as a useful starting point for the full model.

Table 2.3 presents results for the logit specification of the model. The the first column is estimated using standard OLS without instrumenting for price, while the second column is estimated using 2SLS with the price instruments described in Section 2.5.2. As expected, the parameter estimate for price is negative in both cases; but the 2SLS estimate is larger in magnitude. This suggests, at the very least, that failing to address the price endogeneity issue results in an attenuation bias when measuring own-price elasticities. Interestingly, the coefficient on the non-GMO labeling indicator is negative and statistically significantly different from zero in both cases, indicating that use of the label *reduces* the mean utility of consumers. This result is consistent across both regressions and does not change significantly when we instrument for price. It is worth noting, however, that the point estimate for the label indicator is about one-twentieth the magnitude of price; so while the effect is negative, it may not be economically meaningful. In the full model, we will explore this possibility in more detail by simulating the economic effects of different labeling scenarios.

2.6.2 Full Model

The results for the full random coefficients logit model are presented in Table 2.4. The specification includes brand and time (month) fixed effects in addition to the demand parameters listed in the table. The first column presents the mean parameter estimates (β) as well as the taste coefficients estimated using the minimum-distance procedure. The estimate for price is negative, as expected, and about twice the magnitude of the estimate from the logit specification. This indicates higher own-price elasticity, on average. The estimate for the non-GMO labeling indicator is positive and about one-tenth the magnitude of the price estimate. This suggests that use of the label has a slightly positive effect on mean utility and, thus, a brand's market share, which means that firms may have an incentive to seek out the label. Anecdotally, this result seems to coincides with the label's rapid growth between 2010 and 2014. Furthermore, while Adalja (2016) finds no effect of the non-GMO label on price premiums for newly certified non-GMO food products, this result suggests that the effect of the non-GMO label is transmitted via changes in market share.

The additional taste coefficients estimated from the brand fixed effects provide further insight on the drivers of demand. First, the coefficient on organic certification is also positive and of similar magnitude to the non-GMO label coefficient, indicating that both certifications have a similar impact on demand. However, the Non-GMO×Organic interaction term, while similar in magnitude to the organic and non-GMO estimates, is of the opposite sign (negative). This finding would suggest that the two certifications are effectively substitutes in terms of driving demand, and the presence of both certifications on a product does not have an appreciably greater impact on demand.[8] The coefficient estimate for the kids' cereal indicator is positive, as is that for sugar content, which is consistent with past findings in the literature. Interestingly, the estimate for the new product indicator is negative and of similar magnitude to the kids' indicator. To some extent, the extensive product promotion and advertising that tends to accompany the launch of a new RTE cereal product may serve as an effort to overcome this negative effect.

The subsequent columns provide model estimates that characterize individual heterogeneity around the means. The demographic interactions used in the final specification include price interaction terms for income, income squared, and child; label interaction terms for income and age; and constant terms for income and age. Additionally, I estimate standard deviation (σ) for each of the parameters. The signs for the price interaction coefficient estimates indicate that individuals with higher incomes are generally more sensitive to price, which is counterintuitive based

[8] Given that the National Organic Standard prohibits the use of GMO ingredients, it is not terribly surprising that these certifications act as substitutes to some extent; however, the organic certification involves much more than simply using non-GMO ingredients.

on economic theory; however, the impact of an increase of one standard deviation in log income from the average is roughly half that of the price coefficient, so the effect may not be economically meaningful. Individuals under 16 years old are much more sensitive to price than adults, as expected. Lastly, the parameter estimate for the standard deviation of price captures unobserved heterogeneity not explained by demographics.[9]

The signs for the non-GMO label interaction coefficient estimates are straightforward: wealthier individuals as well as older individuals value the non-GMO label less, all else equal. Furthermore, the magnitude of the income interaction estimate is on the same order as the mean parameter estimate for the label, and the estimate for the age interaction is an order of magnitude larger. Therefore, a one-standard deviation increase in log income or age from the sample averages effectively cancels out the positive mean valuation of the label, and beyond that the valuation for non-GMO may become negative. We observe this in the frequency distribution of the individual-specific non-GMO label coefficients in Figure 2.2. Consumer tastes for the non-GMO label coefficient have a wide distribution; and, while the mean valuation is slightly positive, the distribution is rather evenly distributed around zero, suggesting that consumer willingness to pay for non-GMO certified RTE cereal varies significantly.

[9] I also calculate own- and cross-price elasticities from the model using Equation 2.13. The results are intuitive and generally as expected. Since price response is not the primary focus of this paper, median own- and cross-price elasticities are presented in Appendix Tables B.1, B.2, B.3, B.4, and B.5.

2.6.3 Simulated Welfare Effects

To shed light on the potential welfare effects of non-GMO labeling, I simulate two counterfactual labeling scenarios in the RTE cereal industry as outlined in Section 2.5.4: one in which all brands use the non-GMO label over the entire timeframe of the data, and one in which no brands use the label. To establish an initial baseline for comparing the simulations, I first use the demand parameters recovered from the model to construct the price derivative matrix S using Equation 2.12. Then I construct the ownership matrix Ω^o for the 50 brands used in the estimation to calculate price-cost margins using Equation 2.4. Initial mean values for market share, price, marginal cost, price-cost margin, revenue, and profit for each brand, across all 5,988 markets, are presented in Table 2.5.

To simulate each scenario, I simply update the vector x_{jt} to reflect the new labeling scenario, and then calculate new values for the individual component of utility μ_{ijt} using Equation 2.5 and new product market shares using Equation 2.7. With updated market shares, new revenue and profit can be calculated for each brand to assess how each labeling scenario impacts firm profitability. Table 2.6 provides updated mean market share, revenue, profit, and change in profit for each brand, across all 5,988 markets.

The results indicate that complete labeling (Scenario 1) makes most brands worse off than in the initial case. A partial rationale for this result is as follows. Full labeling erodes the market power of firms that previously used the non-GMO label in the initial case such that these brands lose their niche of high-valuation non-GMO consumers to other, less expensive brands that start using the label. At the same time, since the non-GMO label has only a slightly positive effect on mean utility, and many consumers have a net negative valuation for the non-GMO label, complete labeling causes more individuals to choose the outside option. As a result, the original non-GMO RTE cereal brands as well as the newly-labeled conventional brands tend to lose market share and become worse off on average. On the other hand, no labeling (Scenario 2) tends to have an ambiguous effect, with firms both better and worse off. In this scenario, firms that previously used the non-GMO label may be able to maintain some portion of their high-valuation consumer base while also capturing market share of lower-valuation consumers from no-label brands. To the extent that this is possible, some non-GMO RTE cereal brands may become better off at the expense of conventional brands.

To estimate changes to consumer surplus, I use the new values of utility, μ_{ijt}, to calculate the compensating variation [CV] for each scenario, as defined in Equations 2.14 and 2.15 based on our stance regarding decision vs. experience utility, for each individual i in market t. I then take the mean of CV over all 50 individuals for each market t to calculate a market-level mean CV attributable to each labeling scenario. In Table 2.7, I present both the volume-weighted and population-weighted average of mean CV over all 5,988 markets for both CV calculations. If we assume no discrepancy between decision and experience utility, then complete non-GMO labeling in the RTE cereal industry (Scenario 1) reduces consumer welfare across all markets on average. However, when we account for the credence good aspect of non-GMO labeling and incorporate the Leggett (2002) correction, complete non-GMO labeling improves consumer welfare on average. This results indicates that the "cost" of misperception after the policy change is less than the "cost" before the policy change. On the other hand, the results for Scenario 2 indicate that consumers would be worse off with no non-GMO labeling relative to the current baseline, regardless of which calculation is used. In fact, the point estimates are very similar with and without the Leggett correction, since consumers' decision and experience utility effectively converge after the policy change wherein no non-GMO labeled products exist. Given the positive demand parameter estimate for the non-GMO label on the mean utility valuation, this result is rather intuitive.

2.7 Conclusion

In this paper, I investigate how voluntary non-GMO food labeling impacts demand in the RTE cereal industry by estimating a discrete-choice, random coefficients logit demand model with Nielsen Retail Scanner data for 50 breakfast cereal brands in 100 DMAs between 2010 and 2014. The results indicate that consumer tastes for the non-GMO label have a wide distribution, and this heterogeneity plays a substantial role in individual choices; but, on average, the non-GMO label has a positive impact on demand. Organic certification has a similar impact on demand to that of the non-GMO label; however, in combination, the two certifications are effectively substitutes, and the presence of both certifications on a product does not have an appreciably greater impact on demand. To shed light on the potential welfare effects of non-GMO labeling, I simulate two labeling scenarios in the RTE cereal industry: one in which all brands use the non-GMO label over the entire timeframe of the data, and one in which no brands use the label. The simulation results indicate that non-GMO labeling in the RTE cereal industry may improve consumer welfare, but reduce industry profit on average.

The RTE cereal industry has long been a subject of research in empirical industrial organization, with several previous studies investigating the role that non-price strategies such as advertising, couponing, and new product introductions play in the industry (Thomas 1999; Nevo 2001; Nevo and Wolfram 2002). This paper builds on that work and is the first to examine how another non-price marketing strategy—voluntary quality certification—impacts demand in the RTE cereal industry.

Going forward, there are several other considerations and extensions that may benefit this work. First, given the emergent nature of the Non-GMO Project Verified label,[10] consumer learning dynamics may factor significantly into the results. For example, prior to the existence of the non-GMO label, it is quite plausible that most consumers were uninformed about GMOs. As the label began to appear on supermarket shelves, those consumers may have gradually become educated about the label and changed their preferences accordingly. As such, results from a static demand model that does not account for this may have questionable external validity. To accurately capture the effect of consumer learning, it may be necessary to adopt a dynamic framework that incorporates a simple Bayesian learning model (e.g., Ackerberg 2001, 2003). Additionally, there are several complicating dynamics

[10]While the organization was founded in 2005, they only began labeling products in 2010.

worthy of consideration on the supply side as well, such as new product development. As consumers become educated about GMOs, firms may develop new products to meet changing consumer tastes, rather than simply labeling their existing products. While these dynamics are not addressed in the current model, they remain important extensions for future work.

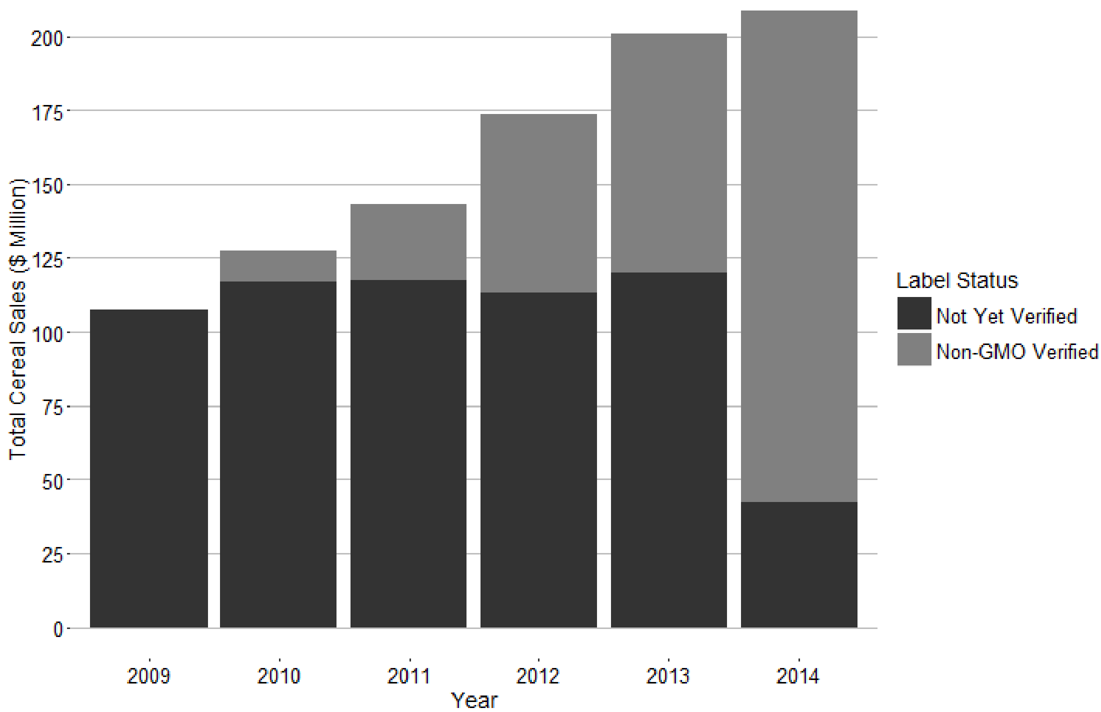


Figure 2.1: Annual Non-GMO Project Verified RTE Cereal Sales

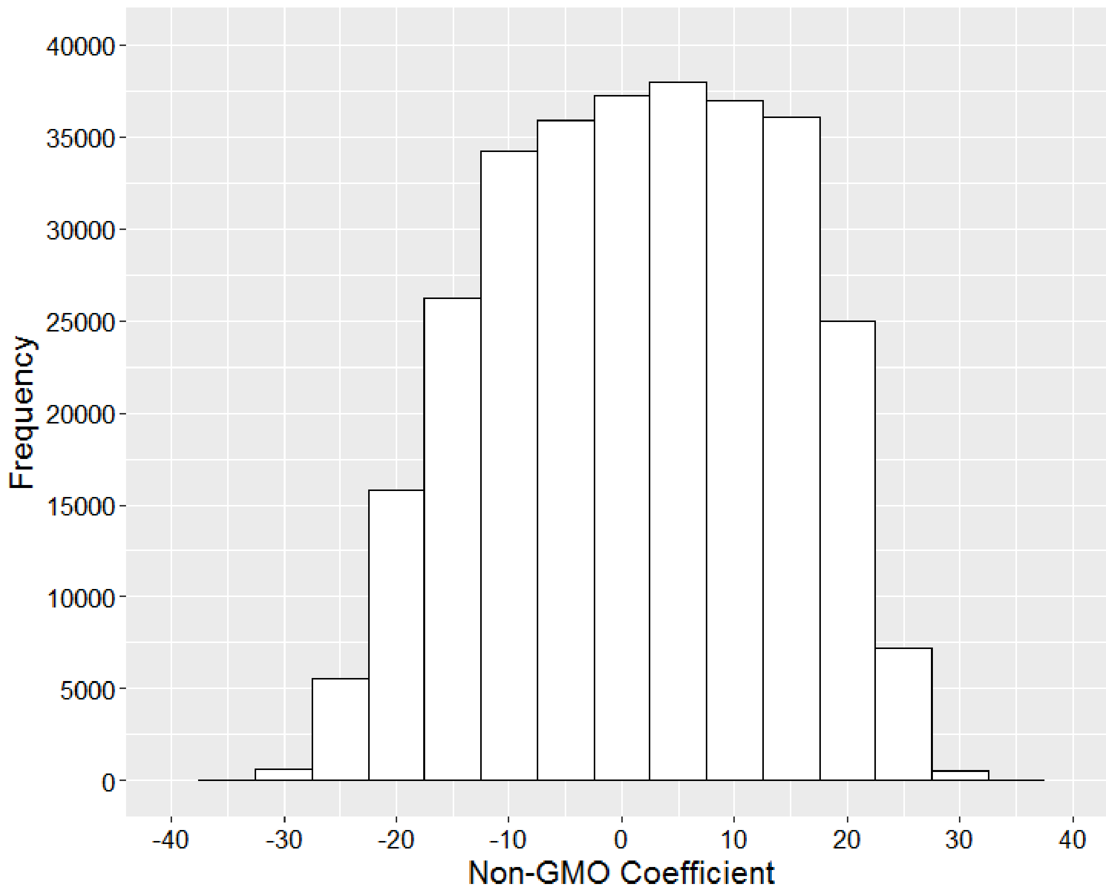


Figure 2.2: Distribution of Non-GMO Label Coefficient

Table 2.1: Summary Statistics

Brand	Non-GMO	Price		Label	Market Share		No.
		Avg.	StDev	Avg.	Avg.	StDev	Markets
01 BARBARA'S PUFFINS	Yes	0.386	0.064	0.296	0.000	0.000	5306
02 G M CHEERIOS	No	0.211	0.019	–	0.013	0.006	5988
03 G M CINNAMON TOAST CRUNCH	No	0.195	0.018	–	0.012	0.005	5988
04 G M COCOA PUFFS	No	0.209	0.021	–	0.003	0.002	5988
05 G M FIBER ONE	No	0.222	0.026	–	0.001	0.001	5988
06 G M HONEY NUT CHEERIOS	No	0.198	0.019	–	0.020	0.008	5988
07 G M HONEY NUT CHEX	No	0.215	0.029	–	0.002	0.001	5988
08 G M LUCKY CHARMS	No	0.209	0.021	–	0.010	0.004	5988
09 G M MULTIGRAIN CHEERIOS	No	0.267	0.026	–	0.005	0.002	5988
10 G M REESE'S PUFFS	No	0.196	0.019	–	0.004	0.002	5988
11 G M RICE CHEX	No	0.238	0.031	–	0.003	0.002	5988
12 KASHI AUTUMN WHEAT PROJECT SPK	Yes	0.199	0.022	1.000	0.001	0.000	3131
13 KASHI CINNAMON HARVEST	Yes	0.203	0.017	0.749	0.001	0.001	4788
14 KASHI GO LEAN	Yes	0.232	0.020	0.017	0.001	0.001	5988
15 KASHI GO LEAN CRISP!	Yes	0.220	0.020	0.182	0.002	0.001	5988
16 KASHI GO LEAN CRUNCH!	Yes	0.217	0.018	0.182	0.003	0.002	5988
17 KASHI HEART TO HEART	No	0.254	0.021	–	0.002	0.001	5988
18 KASHI ISLAND VANILLA	Yes	0.206	0.027	0.595	0.000	0.000	5795
19 KASHI ORGANIC PROMISE ATMN WHT	Yes	0.199	0.020	0.376	0.001	0.000	3846
20 KASHI ORGANIC PROMISE CN HRVST	Yes	0.208	0.022	0.021	0.001	0.001	1226
21 KASHI ORGANIC PROMISE STBY FLD	Yes	0.334	0.050	0.588	0.000	0.000	5759
22 KEL APPLE JACKS	No	0.214	0.026	–	0.005	0.002	5988
23 KEL CORN FLAKES	No	0.187	0.019	–	0.005	0.002	5988
24 KEL FROOT LOOPS	No	0.213	0.023	–	0.008	0.003	5988

Continued...

Table 2.1 – continued from previous page

Brand	Non-GMO	Price Avg.	Price StDev	Label Avg.	Market Share Avg.	Market Share StDev	No. Markets
25 KEL FROSTED FLAKES	No	0.172	0.021	–	0.017	0.008	5988
26 KEL FROSTED MINI-WHEATS	No	0.161	0.014	–	0.016	0.008	5988
27 KEL FROSTED MINI-WHT LTTLE BTS	No	0.193	0.022	–	0.002	0.002	5985
28 KEL RAISIN BRAN	No	0.140	0.015	–	0.009	0.004	5988
29 KEL RAISIN BRAN CRUNCH	No	0.167	0.016	–	0.005	0.002	5988
30 KEL RICE KRISPIES	No	0.222	0.022	–	0.006	0.003	5988
31 KEL SPECIAL K	No	0.234	0.018	–	0.004	0.002	5988
32 KEL SPECIAL K RED BERRY	No	0.242	0.020	–	0.005	0.003	5988
33 KEL SPECIAL K VANILLA ALMOND	No	0.222	0.019	–	0.002	0.001	5988
34 M-O-M FROSTED MINI SPOONERS	No	0.126	0.023	–	0.003	0.003	5972
35 MOM'S BEST NATURALS TSTD WT-FS	Yes	0.122	0.025	–	0.000	0.000	3444
36 NATURE'S PATH FLAX PLUS	Yes	0.271	0.054	0.900	0.000	0.000	5927
37 NATURE'S PATH HERITAGE MLTGN	Yes	0.268	0.058	0.901	0.000	0.000	5661
38 NATURE'S PATH OP PW BRKFST BLB	Yes	0.258	0.050	0.898	0.000	0.000	5829
39 POST GRAPE-NUTS	Yes	0.139	0.017	0.165	0.003	0.002	5988
40 POST HONEY BUNCHES OF OATS	No	0.180	0.016	–	0.017	0.009	5988
41 POST RAISIN BRAN	No	0.128	0.015	–	0.003	0.002	5988
42 POST SELECTS GREAT GRAINS	No	0.201	0.021	–	0.001	0.001	5980
43 POST SHRD WHT 'N BRN SP SZ	Yes	0.188	0.022	0.096	0.001	0.001	5768
44 POST SHREDDED WHEAT SPOON SIZE	Yes	0.179	0.025	0.116	0.001	0.001	5988
45 QKR CINNAMON LIFE	No	0.176	0.021	–	0.004	0.003	5988
46 QKR LIFE	No	0.174	0.021	–	0.005	0.003	5988
47 QKR OATMEAL SQUARES	No	0.199	0.030	–	0.003	0.002	5984
48 UNCLE SAM TSTD WL-WT FLK&FLXSD	Yes	0.310	0.050	0.779	0.000	0.000	5266

Continued...

Table 2.1 – continued from previous page

Brand	Non-GMO	Price		Label	Market Share		No. Markets
		Avg.	StDev	Avg.	Avg.	StDev	
49 UNCLE SAM TSTD WWB FLKS&FLSD	Yes	0.231	0.060	0.982	0.000	0.000	3336
50 KASHI ORGANIC PROMISE BF PS	Yes	0.207	0.018	1.000	0.000	0.000	2454

Table 2.2: Descriptive Statistics for Demographic Variables by DMA

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
PORTLAND-AUBURN ME	0.636	989166	24913	39.4	0.18
NEW YORK NY	0.796	21165376	27046	38.0	0.18
MACON GA	0.839	671423	21953	35.5	0.22
PHILADELPHIA PA	0.731	8046354	26739	37.9	0.21
DETROIT MI	0.796	4837253	25722	37.2	0.18
BOSTON (MANCHESTER) MA-NH	0.653	6430730	23929	39.2	0.18
SAVANNAH GA	0.824	915541	24933	35.6	0.24
PITTSBURGH PA	0.726	2840470	28157	41.1	0.18
FT WAYNE IN	0.819	719204	25937	37.9	0.19
CLEVELAND OH	0.789	3836869	24641	39.8	0.20
WASHINGTON DC (HAGERSTOWN MD)	0.685	6627815	35519	35.7	0.24
BALTIMORE MD	0.716	2945870	32093	37.1	0.17
FLINT-SAGINAW-BAY CITY MI	0.843	1164550	25992	37.9	0.19
BUFFALO NY	0.920	1601355	23100	38.4	0.17
CINCINNATI OH	0.688	2337744	25149	38.5	0.23
CHARLOTTE NC	0.732	3036643	23051	35.0	0.24
GREENSBORO-HIGH POINT-WINSTON SALEM NC	0.775	1760343	25763	40.1	0.18
CHARLESTON SC	0.827	829479	20106	34.4	0.23
AUGUSTA GA	0.809	702247	22787	32.4	0.29
PROVIDENCE-NEW BEDFORD RI-MA	0.804	1604318	25035	37.8	0.22
BURLINGTON-PLATTSBURGH VT-NY	0.759	850630	23682	38.5	0.23
ATLANTA GA	0.831	6517469	25114	35.3	0.22
INDIANAPOLIS IN	0.840	2934588	27729	36.5	0.23

Continued...

Table 2.2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
MIAMI-FT LAUDERDALE FL	0.859	4491338	23845	39.4	0.18
LOUISVILLE KY	0.797	1726671	26683	38.9	0.18
TRI-CITIES TN-VA	0.764	800730	24245	34.9	0.25
ALBANY-SCHENECTADY-TROY NY	0.825	1391414	23921	38.4	0.19
HARTFORD & NEW HAVEN CT	0.843	2657837	26529	38.4	0.19
ORLANDO-DAYTONA BEACH-MELBOURNE FL	0.890	3812030	24164	38.8	0.15
COLUMBUS OH	0.723	2441594	26505	35.4	0.22
YOUNGSTOWN OH	0.807	665768	21974	40.1	0.22
TAMPA-ST PETERSBURG (SARASOTA) FL	0.900	4456924	24682	42.3	0.14
LEXINGTON KY	0.819	1269440	27182	34.1	0.21
DAYTON OH	0.770	1208131	25138	36.6	0.20
NORFOLK-PORTSMOUTH-NEWPORT NEWS VA	0.710	1914660	27071	35.3	0.19
GREENVILLE-NEW BERN-WASHINGTON NC	0.806	805957	19905	28.6	0.30
COLUMBIA SC	0.842	1074481	24916	39.5	0.20
TOLEDO OH	0.813	1068193	22877	37.1	0.20
WEST PALM BEACH-FT PIERCE FL	0.911	1973037	24279	42.2	0.19
WILMINGTON NC	0.755	469138	25637	36.5	0.18
RICHMOND-PETERSBURG VA	0.763	1476812	28114	38.0	0.19
KNOXVILLE TN	0.735	1346498	24070	41.4	0.16
RALEIGH-DURHAM (FAYETTEVILLE) NC	0.726	3011123	27672	33.0	0.24
JACKSONVILLE FL	0.845	1783125	27431	40.1	0.22
CHARLESTON-HUNTINGTON WV	0.841	1160960	24754	34.8	0.26
HARRISBURG-LANCASTER-LEBANON-YORK PA	0.754	1979810	25843	37.1	0.24

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Table 2.2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
GREENVILLE-SPARTANBURG SC-ASHEVILLE NC	0.793	2206893	22206	36.3	0.22
FLORENCE-MYRTLE BEACH SC	0.805	752680	19352	36.5	0.23
FT MYERS-NAPLES FL	0.898	1231514	24841	42.6	0.17
ROANOKE-LYNCHBURG VA	0.745	1143505	27664	36.0	0.18
JOHNSTOWN-ALTOONA PA	0.822	759006	25051	41.8	0.16
CHATTANOOGA TN	0.839	948008	24711	36.8	0.21
SALISBURY MD	0.655	414483	23088	43.4	0.19
WILKES BARRE-SCRANTON PA	0.916	1527611	25122	39.3	0.22
CHICAGO IL	0.734	9685854	25338	35.6	0.26
ST LOUIS MO	0.921	3192777	25628	38.1	0.20
ROCHESTER-MASON CITY-AUSTIN MN-IA	0.719	368385	28720	34.6	0.25
SHREVEPORT LA	0.844	1019171	24818	36.0	0.22
MINNEAPOLIS-ST PAUL MN	0.748	4596920	30219	38.3	0.23
KANSAS CITY MO-KS	0.893	2451398	29849	38.1	0.18
MILWAUKEE WI	0.689	2318553	24953	37.9	0.22
HOUSTON TX	0.839	6555421	26218	32.7	0.26
NEW ORLEANS LA	0.898	1707119	22472	35.6	0.24
DALLAS-FT WORTH TX	0.824	7298112	24431	34.4	0.25
AUSTIN TX	0.944	1979407	22766	34.3	0.23
CEDAR RAPIDS-WATERLOO & DUBUQUE IA	0.802	886337	29867	38.0	0.18
MEMPHIS TN	0.808	1811992	26166	37.8	0.17
OMAHA NE	0.751	1100039	29119	35.5	0.24
GREEN BAY-APPLETON WI	0.799	1129587	27551	36.1	0.25

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Table 2.2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Popula-tion	Average Income	Average Age	Average Child
NASHVILLE TN	0.830	2702008	26633	37.3	0.21
MADISON WI	0.777	971305	23616	33.2	0.26
PEORIA-BLOOMINGTON IL	0.837	647925	29075	39.3	0.22
WICHITA-HUTCHINSON PLUS KS	0.794	1211270	21324	33.9	0.28
DES MOINES-AMES IA	0.800	1121856	25505	34.3	0.25
DAVENPORT-ROCK ISLAND-MOLINE IA-IL	0.819	771658	27057	35.8	0.26
MOBILE-PENSACOLA (FT WALTON BEACH) AL-FL	0.910	1409843	24135	39.1	0.22
LITTLE ROCK-PINE BLUFF AR	0.856	1467596	24790	35.8	0.23
TYLER-LONGVIEW (LUFKIN & NACOGDOCHES) TX	0.842	743180	19016	34.3	0.30
SIOUX FALLS (MITCHELL) SD	0.811	684839	30218	34.6	0.24
DENVER CO	0.683	4167898	28775	35.3	0.21
COLORADO SPRINGS-PUEBLO CO	0.787	937746	23605	40.4	0.25
PHOENIX AZ	0.713	5116720	27898	40.0	0.19
BOISE ID	0.854	744072	23509	37.3	0.24
SALT LAKE CITY UT	0.835	3036126	20127	30.8	0.33
TUCSON (SIERRA VISTA) AZ	0.695	1171202	23292	38.1	0.21
ALBUQUERQUE-SANTA FE NM	0.876	1933926	28213	36.9	0.26
BAKERSFIELD CA	0.764	857730	17657	31.5	0.26
EUGENE OR	0.787	610633	24399	38.6	0.16
LOS ANGELES CA	0.764	18261036	25024	36.6	0.20
SAN FRANCISCO-OAKLAND-SAN JOSE CA	0.728	7090684	29896	37.9	0.16
YAKIMA-PASCO-RICHLAND-KENNEWICK WA	0.823	690790	18166	35.6	0.27
SEATTLE-TACOMA WA	0.709	4931355	31002	35.8	0.23

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Table 2.2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
PORTLAND OR	0.729	3202730	21102	36.9	0.24
SAN DIEGO CA	0.722	3183143	24645	36.6	0.23
MONTEREY-SALINAS CA	0.741	749018	21807	33.9	0.24
LAS VEGAS NV	0.742	2051833	22500	37.6	0.22
SANTA BARBARA-SANTA MARIA CA	0.714	705739	22559	35.1	0.21
SACRAMENTO-STOCKTON-MODESTO CA	0.820	4289848	22477	34.7	0.27
FRESNO-VISALIA CA	0.819	1983349	20782	33.9	0.26
SPOKANE WA	0.849	1126495	27557	39.3	0.19

Table 2.3: Results from the Logit Specification

Variable	OLS	2SLS
Price	-9.218^{***}	-9.815^{***}
	(0.056)	(0.075)
NGMO Label	-0.442^{***}	-0.448^{***}
	(0.008)	(0.008)
Instruments	–	prices
R^2	0.983	0.983
Num. obs.	$277,085$	$277,085$

Note: Each column represents a separate regression. All regressions include brand and month fixed effects. Standard errors are in parentheses: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 2.4: Full Model Results

Variable	Means β	StDev σ	Intxn with Demographic Vars Income	IncomeSq	Age	Child
Price	-17.679	1.531	-8.107	-9.913		-64.246
NGMO Label	1.386	2.904	-1.987		-11.498	
Constant	-14.902[a] (1.228)	2.609	8.995		7.075	
Organic	1.293[a] (0.043)					
Non-GMO×Organic	-1.530[a] (0.051)					
Kids	0.486[a] (0.018)					
Sugar	0.018[a] (0.001)					
New Product	-0.546[a] (0.043)					
GMM Obj.			0.147			
No. Obs.			277,085			

[a] Estimated using a minimum-distance procedure.

Note: Unless otherwise specified, all parameters are GMM estimates. All regressions include brand and month fixed effects. Standard errors are in parentheses.

Table 2.5: Initial Baseline for Simulation

Brand	Market Share	Price	Marginal Cost	Margin	% Margin	Revenue	Profit
1	0.0003	0.3571	0.6076	-0.2505	-0.8400	0.0001	0.0000
2	0.0161	0.2104	0.0096	0.2009	0.9238	0.0034	0.0033
3	0.0146	0.1910	0.1082	0.0828	0.4350	0.0027	0.0012
4	0.0045	0.2024	0.0787	0.1237	0.5998	0.0009	0.0005
5	0.0020	0.2224	-0.1702	0.3926	1.6803	0.0004	0.0007
6	0.0244	0.1938	0.1087	0.0850	0.4362	0.0047	0.0020
7	0.0026	0.2068	0.1289	0.0779	0.3847	0.0005	0.0002
8	0.0114	0.2047	-0.0451	0.2498	1.1767	0.0023	0.0027
9	0.0057	0.2632	0.1580	0.1052	0.4113	0.0015	0.0007
10	0.0053	0.1911	0.1038	0.0873	0.4527	0.0010	0.0005
11	0.0042	0.2251	0.1393	0.0858	0.3609	0.0009	0.0003
12	0.0008	0.2006	0.1432	0.0575	0.2750	0.0002	0.0001
13	0.0013	0.2009	0.1582	0.0427	0.2141	0.0003	0.0001
14	0.0017	0.2315	0.3026	-0.0711	-0.2681	0.0004	-0.0001
15	0.0022	0.2164	0.1159	0.1005	0.4549	0.0005	0.0002
16	0.0040	0.2151	0.1062	0.1088	0.5038	0.0009	0.0005
17	0.0025	0.2532	0.2519	0.0013	0.0274	0.0006	0.0001
18	0.0005	0.2014	0.1091	0.0923	0.4464	0.0001	0.0000
19	0.0010	0.1991	0.2892	-0.0901	-0.5139	0.0002	0.0000
20	0.0014	0.2024	0.1376	0.0649	0.3269	0.0003	0.0001
21	0.0003	0.3326	0.5123	-0.1797	-0.5431	0.0001	-0.0001
22	0.0059	0.2068	0.0479	0.1589	0.6959	0.0012	0.0008
23	0.0062	0.1836	0.1090	0.0747	0.4021	0.0011	0.0004
24	0.0091	0.2064	0.1070	0.0994	0.4666	0.0018	0.0009
25	0.0207	0.1656	0.1040	0.0617	0.3755	0.0034	0.0012
26	0.0188	0.1587	0.1014	0.0572	0.3529	0.0029	0.0010
27	0.0032	0.1885	0.1087	0.0798	0.4191	0.0006	0.0003
28	0.0116	0.1359	0.0809	0.0550	0.4055	0.0015	0.0006
29	0.0055	0.1646	0.1044	0.0601	0.3565	0.0009	0.0003
30	0.0070	0.2182	0.1061	0.1121	0.5106	0.0015	0.0008
31	0.0056	0.2336	-0.3699	0.6035	2.5115	0.0013	0.0032
32	0.0068	0.2384	0.3597	-0.1214	-0.4742	0.0016	-0.0007
33	0.0028	0.2210	1.0154	-0.7944	-3.1855	0.0006	-0.0024
34	0.0066	0.1145	0.0834	0.0311	0.2978	0.0006	0.0002
35	0.0003	0.1139	0.0853	0.0285	0.2577	0.0000	0.0000
36	0.0003	0.2548	0.4187	-0.1639	-0.5812	0.0001	-0.0000
37	0.0003	0.2497	0.2932	-0.0435	-0.2504	0.0001	0.0000
38	0.0002	0.2310	0.2062	0.0247	0.1461	0.0000	0.0000
39	0.0041	0.1382	0.0973	0.0409	0.2967	0.0005	0.0002

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Table 2.5 – continued from previous page

Brand	Market Share	Price	Marginal Cost	Margin	% Margin	Revenue	Profit
40	0.0238	0.1763	0.1288	0.0476	0.2725	0.0042	0.0012
41	0.0038	0.1233	0.0870	0.0364	0.3010	0.0004	0.0001
42	0.0022	0.1954	0.1428	0.0526	0.2776	0.0004	0.0001
43	0.0014	0.1872	0.1267	0.0605	0.3204	0.0003	0.0001
44	0.0022	0.1769	0.1215	0.0554	0.3112	0.0004	0.0001
45	0.0060	0.1688	0.1237	0.0451	0.2673	0.0010	0.0003
46	0.0077	0.1693	0.1260	0.0433	0.2585	0.0013	0.0003
47	0.0051	0.1947	0.1339	0.0608	0.3095	0.0010	0.0003
48	0.0002	0.2944	0.3284	-0.0340	-0.1055	0.0000	-0.0000
49	0.0002	0.2162	0.0564	0.1598	0.7458	0.0001	0.0000
50	0.0006	0.2069	0.1144	0.0925	0.4729	0.0001	0.0001

Note: The values in each column represent the intial volume-weighted mean values of a given variable for each brand, across all 5,988 markets.

Table 2.6: Simulated Labeling Scenario Results

Brand	1: Complete Labeling				2: No Labeling			
	Market Share	Revenue	Profit	Profit Chg	Market Share	Revenue	Profit	Profit Chg
1	0.0009	0.0004	-0.0001	-0.0001	0.0006	0.0002	-0.0001	-0.0001
2	0.0064	0.0013	0.0012	-0.0021	0.0153	0.0032	0.0032	-0.0000
3	0.0057	0.0011	0.0005	-0.0007	0.0140	0.0026	0.0012	-0.0000
4	0.0017	0.0003	0.0002	-0.0003	0.0043	0.0009	0.0005	-0.0000
5	0.0008	0.0002	0.0002	-0.0005	0.0019	0.0004	0.0007	-0.0000
6	0.0094	0.0018	0.0008	-0.0012	0.0233	0.0045	0.0019	-0.0001
7	0.0009	0.0002	0.0001	-0.0001	0.0024	0.0005	0.0002	-0.0000
8	0.0044	0.0009	0.0010	-0.0017	0.0108	0.0022	0.0026	-0.0000
9	0.0032	0.0008	0.0008	0.0001	0.0054	0.0014	0.0007	-0.0000
10	0.0019	0.0004	0.0002	-0.0003	0.0050	0.0009	0.0004	-0.0000
11	0.0016	0.0003	0.0001	-0.0001	0.0039	0.0008	0.0003	-0.0000
12	0.0003	0.0001	0.0000	-0.0000	0.0040	0.0008	-0.0010	-0.0011
13	0.0005	0.0001	0.0000	-0.0001	0.0052	0.0010	-0.0012	-0.0012
14	0.0008	0.0002	-0.0000	0.0001	0.0016	0.0004	-0.0001	-0.0000
15	0.0008	0.0002	0.0001	-0.0001	0.0025	0.0005	0.0004	0.0002
16	0.0016	0.0004	0.0002	-0.0002	0.0043	0.0009	0.0005	0.0000
17	0.0013	0.0003	0.0001	-0.0000	0.0024	0.0006	0.0001	0.0000
18	0.0002	0.0000	0.0000	-0.0000	0.0016	0.0003	0.0004	0.0004
19	0.0004	0.0001	0.0000	0.0000	0.0016	0.0003	0.0000	0.0000
20	0.0007	0.0001	0.0001	-0.0000	0.0014	0.0003	0.0001	0.0000
21	0.0005	0.0002	-0.0003	-0.0003	0.0006	0.0002	-0.0002	-0.0001
22	0.0023	0.0005	0.0003	-0.0005	0.0056	0.0011	0.0007	-0.0000
23	0.0023	0.0004	0.0002	-0.0002	0.0059	0.0011	0.0004	-0.0000

Continued...

Table 2.6 – continued from previous page

Brand	1: Complete Labeling				2: No Labeling			
	Market Share	Revenue	Profit	Profit Chg	Market Share	Revenue	Profit	Profit Chg
24	0.0035	0.0007	0.0003	-0.0005	0.0086	0.0017	0.0008	-0.0000
25	0.0079	0.0013	0.0006	-0.0007	0.0198	0.0032	0.0012	-0.0001
26	0.0073	0.0011	0.0005	-0.0005	0.0180	0.0028	0.0010	-0.0000
27	0.0011	0.0002	0.0001	-0.0001	0.0030	0.0006	0.0002	-0.0000
28	0.0051	0.0007	0.0003	-0.0003	0.0111	0.0015	0.0006	-0.0000
29	0.0021	0.0003	0.0001	-0.0002	0.0053	0.0008	0.0003	-0.0000
30	0.0027	0.0006	0.0004	-0.0005	0.0066	0.0014	0.0008	0.0000
31	0.0023	0.0005	0.0003	-0.0029	0.0054	0.0012	0.0029	-0.0003
32	0.0030	0.0007	-0.0003	0.0004	0.0065	0.0015	-0.0007	0.0000
33	0.0011	0.0002	-0.0017	0.0006	0.0027	0.0006	-0.0024	-0.0000
34	0.0039	0.0003	0.0001	-0.0001	0.0064	0.0006	0.0002	-0.0000
35	0.0002	0.0000	0.0000	-0.0000	0.0003	0.0000	0.0000	-0.0000
36	0.0001	0.0000	-0.0000	0.0000	0.0009	0.0002	-0.0001	-0.0000
37	0.0001	0.0000	0.0000	-0.0000	0.0009	0.0002	-0.0000	-0.0001
38	0.0001	0.0000	0.0000	-0.0000	0.0006	0.0001	0.0000	0.0000
39	0.0019	0.0002	0.0001	-0.0001	0.0050	0.0007	0.0002	0.0001
40	0.0093	0.0016	0.0004	-0.0007	0.0230	0.0040	0.0011	-0.0000
41	0.0021	0.0002	0.0001	-0.0001	0.0036	0.0004	0.0001	-0.0000
42	0.0009	0.0002	0.0001	-0.0001	0.0021	0.0004	0.0001	-0.0000
43	0.0006	0.0001	0.0000	-0.0000	0.0016	0.0003	0.0001	-0.0000
44	0.0009	0.0002	0.0001	-0.0001	0.0023	0.0004	0.0001	0.0000
45	0.0024	0.0004	0.0001	-0.0002	0.0058	0.0009	0.0003	-0.0000
46	0.0031	0.0005	0.0001	-0.0002	0.0074	0.0012	0.0003	-0.0000

Continued...

Table 2.6 – continued from previous page

Brand	1: Complete Labeling				2: No Labeling			
	Market Share	Revenue	Profit	Profit Chg	Market Share	Revenue	Profit	Profit Chg
47	0.0019	0.0004	0.0001	-0.0002	0.0049	0.0009	0.0003	-0.0000
48	0.0001	0.0000	-0.0000	-0.0000	0.0006	0.0002	0.0001	0.0001
49	0.0001	0.0000	0.0000	-0.0000	0.0012	0.0002	0.0002	0.0002
50	0.0002	0.0000	0.0000	-0.0001	0.0028	0.0006	0.0002	0.0002

Note: The values in each column represent the mean volume-weighted values of a given variable in the simulated scenario for each brand, across all 5,988 markets.

Table 2.7: Welfare Effects of Simulated Labeling Scenarios

Variable	Scenario 1: Complete Labeling		Scenario 2: No Labeling	
	No Correction	Leggett Correction	No Correction	Leggett Correction
Volume-Weighted Mean CV	-0.08708	0.00933	-0.01496	-0.01468
Population-Weighted Mean CV	-0.03151	0.03248	-0.01450	-0.01385

Note: To calculate Mean CV, individual compensating variation, as defined in Equation 2.14 and Equation 2.15, is averaged over all 50 individuals in a given market t. A weighted-average of Mean CV is then calculated over all 5,988 markets.

Chapter 3: Produce Growers' Cost of Complying with the Food Safety Modernization Act*,†

3.1 Introduction

The enactment of the Food Safety Modernization Act [FSMA] gave the Food and Drug Administration [FDA] authority to regulate the growing, harvesting, packing, and holding of fresh fruits and vegetables and represents a major shift in the agency's approach from outbreak response to prevention-based controls across the food supply. Data from the Centers for Disease Control and Prevention indicate that fruits and vegetables accounted for 46% of foodborne illness outbreaks during the period 1998-2008, a larger share than any other category of food (Painter 2013). As one of the implementing rules for FSMA, the FDA has implemented a rule (known popularly as the Produce Rule) intended to reduce health risks associated with foodborne illness from consumption of fresh produce. That rule, which became effective in January of 2016, requires operational changes to meet standards asso-

*This chapter is co-authored with Erik Lichtenberg, Department of Agricultural and Resource Economics, University of Maryland, College Park.

†This material is based upon research supported by the National Institute of Food and Agriculture, Specialty Crop Research Initiative, Award No. 2011-51181-30767. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of the U.S. Department of Agriculture.

ciated with agricultural water; biological soil amendments; domesticated and wild animals; employee training and health and hygiene; and equipment, tools, buildings, and sanitation. Those changes could be costly.

Small farms and sustainable growers have voiced fears that the Rule will have adverse competitive effects. Small farms worry that the costs of complying with the new rule may be disproportionately burdensome and could drive them out of business (Hassanein 2011; Paggi et al. 2013; Knutson et al. 2014; Ribera et al. 2016). Farms employing sustainable agricultural practices are concerned that the Rule may make it impossible for them to use the biological soil amendments and livestock grazing practices in integrated agricultural systems on which they currently rely. Both concerns suggest that the Rule may adversely affect important segments of the produce industry (Ribera and Knutson 2011) that are subject to an increasing focus nationwide in terms of marketing, consumption, and federal policy (Low 2015).

There is very little publicly available information on the likely cost of the actions required under the new Rule. To help fill that information gap, we use data from an original national survey of fruit and vegetable growers and construct a larger sample than most comparable studies. We examine whether compliance with the standards in the Produce Rule is likely to be disproportionately burdensome to small and/or sustainable farm operations. To investigate that question, we analyze how the costs of food safety practices required by the Produce Rule vary with farm size and use of sustainable farming practices using a double hurdle model to control for selectivity in both using food safety practices and reporting expenditures on them. We use our estimates to quantify how the cost burden of compliance varies with farm size. We then explore the policy implications of exemptions to the Rule by simulating how changes to the exemption thresholds for farm revenue and share of direct sales might affect the cost burden of each food safety practice on farms at the threshold.

3.2 Background

3.2.1 Relevant Literature

Several recent studies analyze the costs of implementing practices made mandatory by the new on-farm produce safety standards. Hardesty and Kusunose (2009) use data from a survey of 49 California growers to estimate the compliance costs for food safety standards imposed by the California Leafy Greens Marketing Agreement [LGMA], which are similar to those required under the proposed Produce Rule. They find that growers' seasonal food safety costs more than doubled after implementation of the LGMA, and the largest growers benefit from significant economies of scale. Ribera et al. (2012) conduct three case studies of food safety outbreaks in muskmelon, spinach, and tomatoes and use a survey of producers participating in the California LGMA to estimate the compliance costs for new food safety standards. They find that the costs incurred by producers due to food safety outbreaks are much greater than LGMA compliance costs, and the most significant compliance cost increases are attributable to third party audits, staffing, and water testing. Paggi et al. (2013) use results from several studies to develop an example of the impact and compliance costs of LGMA-type standards for Florida cabbage producers and find that for a representative grower, the probability of operating at a net loss (in present value terms) over a 2-year period increased by 17%. To assess the impacts from FSMA, Ribera et al. (2014) develop representative farms for cabbage, cantaloupe, citrus, onion, spinach, tomato, and watermelon production in California, Florida, and Texas. They find that the cost of complying with the Produce Rule is not size neutral and can have negative impacts on the profitability of small farms. A University of Minnesota study uses data collected from in-person and telephone interviews with small and mid-sized vegetable farmers to estimate total costs incurred for Minnesota vegetable growers to adopt GAPs practices on their farms (Driven to Discover 2012). The study also finds that compliance costs exhibit significant economies of scale—small farms in Minnesota would face food safety costs equal to 10% of gross revenue, while average-sized farm operations would incur costs around 2% of gross revenue. Lichtenberg and Page (2016) use data from a survey of Mid-Atlantic leafy greens and tomato growers to assess the likely cost burden of adopting on-farm food safety measures like those required under FSMA. They find substantial economies of scale but a fairly modest cost burden on farms of all sizes.

Concerns about the burdens imposed on small producers—and the resulting potential for increased industry concentration—have been recurring issues in discussions of food safety regulation. In the late 1990s, compliance with Hazard Analysis and Critical Control Points (HACCP) regulations in meat packing and processing was believed to exhibit economies of scale because large firms had in-house testing facilities, technicians, and other investments in physical and human capital that small firms did not have, as well as being able to benefit from bulk discounts for outside testing services (MacDonald and Crutchfield 1996; Loader and Hobbs 1999; Unnevehr and Jensen 1999; Antle 1999). Similarly, the cost burden of adopting global ISO 9000 food safety certification standards was thought to involve proportionally greater resources for small firms than large ones (Holleran et al. 1999).

The empirical evidence on this score is decidedly mixed. An econometric analysis by Antle (2000) found no evidence of differences in HACCP compliance costs in U.S. beef, pork, and poultry processing. An econometric study by Hooker et al. (2002), by contrast, found that small meat processors incurred higher compliance costs, while Muth et al. (2003) found that meat and poultry plants classified as small or very small under HACCP regulations were more likely to exit during the period of HACCP implementation, although the differential effect of regulation on exit by plant size was quantitatively quite small.

3.2.2 The Food Safety Modernization Act and the Produce Rule

FSMA was signed into law in January of 2011. While a growing number of supermarket chains, commodity group organizations and others had been instituting private food standards for food quality and safety over the preceding decade, a series of bacterial outbreaks during the mid-2000s indicated that such voluntary efforts would be insufficient to provide adequate levels of safety (Henson and Reardon 2005; Paggi et al. 2013). The FDA published the original proposed Produce Rule, officially known as *Standards for the Growing, Harvesting, Packing, and Holding of Produce for Human Consumption*, in January of 2013. The Rule was finalized in

November of 2015[3] and became effective in January of 2016. It establishes standards across various aspects of agricultural production, most notably with regards to: (1) agricultural water; (2) biological soil amendments of animal origin; (3) health and hygiene; (4) intrusion of domesticated and wild animals; and (5) sanitation of equipment, tools, and buildings.

For agricultural water that contacts produce or food-contact surfaces, the Rule establishes quality standards, periodic inspection and testing provisions, and treatment requirements for water not meeting sanitary standards. For soil amendments of animal origin, the Rule establishes treatment standards and application requirements for treated and untreated soil amendments. For health and hygiene, the rule establishes hygienic practices and training requirements for all farm personnel who handle produce covered by the Rule. For intrusion of domesticated and wild animals, the Rule establishes waiting periods between grazing and crop harvest for domesticated animals and monitoring requirements for wild animal intrusion. Lastly, the Rule establishes sanitary standards for equipment and tools that come in contact with produce, as well as requirements for pest control, hand washing and toilet facilities, and sewage and trash disposal. In addition to these measures, the Rule also requires recordkeeping and documentation to show compliance with each standard.

The Produce Rule applies to farms that grow and sell produce usually consumed raw and not intended for commercial processing (e.g., canning, etc.). Farms whose annual produce sales averaged less than $25,000 during the preceding three

[3] The FDA revised the Rule twice in the interim period, each time based on feedback from a public comment period.

years are exempt. Farms that have three-year annual produce sales of less than $500,000 and sell a majority of food directly to a qualified end-user—a consumer, restaurant, or retail food establishment (e.g., a supermarket, etc.) located in-state or within 275 miles of the farm—are not subject to the food safety standards in the Rule.[4] Additionally, the compliance dates in the Rule allow more time for smaller farms to adopt the established safety provisions. Farms with annual produce sales between $25,000 and $250,000—classified as "very small" farms in the Rule—have four years after the Rule's effective date to comply with most provisions. Farms with annual produce sales between $250,000 and $500,000—classified as "small" farms in the Rule—have three years. Farms with annual produce sales over $500,000[5] have two years. Furthermore, the compliance dates for water quality standards (including testing and recordkeeping) are an additional two years after the compliance dates for the rest of the Rule.

3.3 Data

3.3.1 Survey Design

We use data from an original national survey of fruit and vegetable growers to analyze the likely cost burden of produce safety measures required under the Product Rule.[6] The survey includes background questions on farm economics, farm

[4]This provision is an amendment to FSMA introduced by Senators Jon Tester and Kay Hagan and is commonly referred to as the Tester-Hagan Exemption or, more formally, direct marketing modified requirements.

[5]The Produce Rule does not designate a name for farms that fall into this category, so we refer to them as "medium/large" farms throughout the text and tables.

[6]Appendix C.2 includes a full version of the survey instrument used.

characteristics, and use of marketing channels in addition to questions regarding use and treatment of soil amendments, microbial testing, field monitoring, remedial food safety actions, preventive food safety actions, and recordkeeping. Soil amendment questions covered whether animal-based soil amendments were used; whether they were treated, and if so, at what cost; and the time interval between application of soil amendments and crop harvest. Microbial testing questions covered whether the farm collected water, soil amendment, and/or crop samples for testing, and if so, at what cost (including employee wages, materials, etc.). Field monitoring questions covered whether the fields were monitored for animal intrusion, flooding, and/or other contamination; how often these events were observed; and the costs associated with monitoring the fields. Remedial action food safety questions covered whether any remedial actions (e.g., sanitation, product disposal, water treatment, etc.) were taken following test results, flooding, and/or animal intrusion, and if so, at what cost. Preventive food safety questions covered whether harvest containers were sanitized prior to harvest or if new containers were used, whether crops were washed prior to sale, whether the farm used third party food safety audits, and whether precautions were taken with regards to employee sanitation and hygiene (e.g., training, tool sanitation, toilet and hand washing facilities, etc.). Lastly, recordkeeping questions covered whether the farm kept written records for food safety practices, and if so, how many hours each week were spent doing so.

3.3.2 Survey Administration

The survey was designed and administered electronically using Qualtrics survey software. It included skip logic so respondents only answered questions relevant to their farm operation. Data was collected in person at eight major fruit and vegetable grower conferences across the U.S. and through online grower listservs provided by several state fruit and vegetable growers' associations, university extension services, and other grower organizations via a password-protected Internet survey. To address concerns related to the Rule's impact on sustainable growers, we also surveyed members of listservs for several sustainable grower organizations and attendees at a major sustainable grower conference.[7] At the conferences, a booth was set up alongside other exhibitors in the trade show or a similar high traffic area, and attendees passing by the booth were asked to participate in the survey, after which they could enter a drawing for a chance to win an Apple iPad. After consenting to participate, respondents completed the fifteen-minute survey on tablet computers, providing information about the 2014 growing season. Upon completing the survey, the software automatically redirected each respondent to a separate form in which she could choose to enter the iPad drawing.

The survey sent to grower listservs was identical to the version administered at the grower conferences, except that respondents completed the survey independently on their own web-enabled device, typically either a personal computer or tablet. Members of each listserv were sent an email soliciting their participation in the

[7] Appendix C.1 includes detailed lists of grower conferences and online listservs from which responses were collected.

survey. Each email included a description of the survey and research goal, informed consent agreement, our contact information, and a web link and password to take the survey. We used the password to identify the listserv through which the respondent was contacted. The survey software uses browser cookies to prevent respondents from taking the survey more than once. As an incentive to participate, online respondents were given the same offer to enter a drawing for an iPad after completing the survey. All the survey collectors for the grower listservs remained open until May 2, 2015.

3.3.3 Summary Statistics

In total, 394 growers completed the survey. A large majority (277, about 70%) came from listservs while the remainder (117, about 30%) completed the survey at a grower convention (Table 3.1). Almost 80% of the respondents (311) grow vegetables, 193 grow berries, and 194 grow fruit and tree nuts (many growers raise produce from more than one category).

Our sample is weighted towards commercial-size farms compared to the 2012 USDA Agricultural Census as measured by revenue and acreage (Figure 3.1). In terms of regional distribution, our sample consists of relatively more farms in the Northeast and South and fewer farms in the West than the U.S. as a whole (Table 3.2). The West consists of states that represent a significant portion of large fruit and vegetable agribusiness growers in the U.S. (e.g., California, Arizona, etc.) that account for a majority of the produce consumed nationwide. Many of these

Western growers were already obligated to meet food safety standards under the LGMA, which are quite similar to those required under the Produce Rule. The geographic distribution of respondents suggests that, while our sample may be less representative of total U.S. fruit and vegetable *production*, it is more representative of the population of U.S. produce *growers* likely to be affected by the Produce Rule, which is ultimately of greater relevance to the issues we wish to address.

Overall, one-third of our sample comes from members of sustainable grower organizations,[8] with the balance comprised of members of conventional grower organizations. In terms of farm size, sustainable growers in our sample tend to operate smaller farms than conventional growers, with about half of sustainable growers falling into the exempt farm classification compared to just over a quarter of conventional growers (Table 3.3). On average, growers in our sample sell more than half their produce directly to consumers (Table 3.1).

Respondents from grower conventions and listservs are quite similar in most respects, the major difference being that almost all respondents identified as sustainable came from listservs. Likely for that reason, respondents from conventions are slightly larger, sell less of their output direct to consumers, do more sampling and testing, and are a little less likely to be diversified. All of those differences are small, however.

Based on current sales and practices, over three-fourths of our sample are exempt from the Produce Rule, which is almost evenly split based on the farm size

[8] To be concise, we refer to members of sustainable grower organizations as "sustainable growers" and members of conventional grower organizations as "conventional growers" throughout the text.

and the Tester-Hagan exemptions (Table 3.3). Almost all very small growers and three-fourths of small growers in our sample qualify for the Tester-Hagan exemption. In terms of farming practices, nearly all sustainable growers in our sample qualify for an exemption, with over half exempt based on size, and about two-thirds of conventional growers are exempt.

3.4 Profit Maximizing Choice of Food Safety Practices: Theory and Econometric Specification of Expenditures

We are interested in how the costs of implementing food safety practices required under the Produce Rule vary with respect to farm size. To fix ideas, consider a grower using productive inputs $X_1, \ldots, X_J$ and food safety practices $Z_1, \ldots, Z_K$ to produce a vector of marketable outputs $\mathbf{Y}$ on a farm of fixed acreage A using a technology represented by a transformation function $f(\mathbf{Y}, \mathbf{X}, \mathbf{Z}; A) \leq 0$. Here marketable output represents a combination of quantity and perceived quality (i.e., marketable outputs can differ in terms of quality (locally grown, sustainably grown, heirloom variety, etc.) and thus price received).

The grower wants to maximize profit:

$$\pi = \mathbf{pY} - \mathbf{wX} - \mathbf{vZ} - \mathbf{F} \quad \text{s.t.} \quad f(\mathbf{Y}, \mathbf{X}, \mathbf{Z}; A) \leq 0 \tag{3.1}$$

where $\mathbf{p}$, $\mathbf{w}$, $\mathbf{v}$, and $\mathbf{F}$ are vectors of output prices, input prices, food safety practice costs, and fixed costs, respectively. The necessary conditions imply optimal use of productive inputs $X_j^*(\mathbf{p}, \mathbf{w}, \mathbf{v}; A)$ and food safety practices $Z_k^*(\mathbf{p}, \mathbf{w}, \mathbf{v}; A)$. Expenditure on food safety practice k is

$$e_k = v_k Z_k^*.$$

The change in expenditure on food safety practice k with respect to farm size A is

$$\frac{\partial e_k}{\partial A} = v_k \frac{\partial Z_k}{\partial A} = \frac{v_k Z_k}{A} \frac{\partial Z_k}{\partial A} \frac{A}{Z_k}$$

The elasticity of expenditure on food safety practice k with respect to farm size A is thus

$$\eta_k \equiv \frac{A}{e_k} \frac{\partial e_k}{\partial A} = \frac{\frac{\partial Z_k}{\partial A}}{\frac{Z_k}{A}} \tag{3.2}$$

If the marginal change in use of food safety practice k as size (acreage) increases is less than the average, then expenditure on food safety practice k is inelastic. Inelastic expenditure on a food safety practice implies that larger operations spend less per acre than smaller ones; elastic expenditure implies that larger operations spend more per acre than smaller ones; and unit elastic expenditure implies that expenditure per acre is constant (invariant with respect to acreage).

Since we are interested in estimating the elasticities of food safety practices required under the Produce Rule, we assume a log-linear specification of expenditures.

For grower j, we have

$$\log(e_{jk}) = \beta_k + \sum_i \gamma_i T_{ji} + \eta_k \log(A_j) + u_{jk} \tag{3.3}$$

Here T_{ji} represents variables like crop type and an indicator for sustainable farming practices assumed to shift expenditures on average and u_{jk} is a normally distributed white noise error representing all unobservables that influence expenditure on food safety practice k. We are especially interested in the coefficient of the "sustainable" indicator, i.e., average differences in compliance cost between conventional and sustainable growers, since the latter have been among the most vocal in expressing concerns about the impacts of compliance with the Produce Rule on their operations.

For food safety measures that are part of a larger group of practices (e.g., employee training is one action in employee sanitation and hygiene, etc.), we streamlined the survey by asking respondents to provide total cost estimates for the overall group of food safety practices: all forms of testing, all field inspections, all harvest container sanitation measures, all employee sanitation and hygiene measures, and treatment of all soil amendments. For these food safety practices, we control for each specific action by including indicator variables for each type of action used by the grower. For these groups of practices, we specify expenditures as

$$\log(e_{jk}) = \beta_k + \sum_m (\beta_{km} P_{jkm}) + \sum_i \gamma_i T_{ji} + \log(A_j) \sum_m (P_{jkm} \eta_{km}) + u_{jk} \tag{3.4}$$

where P_{jkm} is an indicator variable taking on a value of 1 if grower j uses individual action m within the group of practices k. To assess robustness, we also estimate a model where the elasticities of all practices within a group are assumed equal, as specified in Equation 3.3.

3.5 Estimation Method

Estimating the parameters of the models specified in the preceding section is complicated by two factors: (1) we observe cost only for growers who actually use a food safety practice and (2) some growers who used a food safety practice did not report cost. For example, between 6% and 22% of respondents in our sample reported not using one or more of these practices, with as many as 40-60% reporting not doing any sampling, inspection, or third party audits. Of those who reported using these food safety practices, between 5% and 30% failed to report cost. Not surprisingly, non-response rates for cost were substantially higher among respondents who completed the survey at grower conventions (20-50% of users) than those responding from listserv solicitations (3-17% of users).

It is likely that unobserved factors affect the probability of a grower using a specific food safety practice, the cost of implementing that practice, and the probability that a grower fails to report the cost of that practice. We therefore estimate a double hurdle model to control for potential selection bias from both non-use and non-reporting among users. We specify the probability that grower j uses food safety practice (or group of food safety practices) k as

$$\Pr(v_{jk} \leq \xi_k + \mu_k O_j + \sum_i \zeta_i T_{ji} + \theta_k \log(A_j)) = \Phi(\xi_k + \mu_k O_j + \sum_i \zeta_i T_{ji} + \theta_k \log(A_j)) \quad (3.5)$$

where v_{jk} is a normally distributed white noise error representing all unobservables that influence the choice of whether to use food safety practice k, and $\Phi(\cdot)$ denotes a standard normal cumulative distribution.

The selection equation contains two variable not included in the expenditure equation: O_j, an indicator taking on a value of 1 if grower j has a contractual obligation to use one or more food safety practices, and the share of output sold to wholesalers/repackers, mass merchandisers, exporters, brokers, or other outlets (included in the set of grower characteristics T_{ji}). These two variables thus serve as instruments to identify selection.

A substantial theoretical literature suggests that marketing channels may be important in creating incentives for growers to adopt food safety practices (Henson and Caswell 1999; Segerson 1999; Fares and Rouviere 2010; Hennessy et al. 2001; Henson and Reardon 2005; Fulponi 2006; Carriquiry and Babcock 2007; Rouvière and Caswell 2012). A foodborne illness outbreak can damage the reputation of a downstream agent that sells directly to consumers (such as a grocery store or restaurant), and, if a seller is found liable, can result in direct financial losses as well. Therefore, in some marketing channels downstream buyers may require produce growers to use certain food safety practices, motivating our use of O_j as an instrument for selection. Farmers that sell all of their output direct to consumers have no contractual obligations; about 27% of farmers with some direct sales fall into this category and are thus recorded as having no contractual obligations to use any food safety practices. ($O_j = 0$ if the share of direct sales = 100%). To avoid collinearity, we omit the share of output sold to grocery retailers and foodservice operations, which are primarily local and thus have a high degree of traceability and large reputation effects. The same considerations lead us to drop the share of output sold direct to consumers from the selection equation as well.

We include the indicator of sustainable production practices in the selection equation to examine how sustainable and conventional growers differ in their use of food safety practices. There is considerable evidence that consumers view sustainably grown food as safer than conventionally grown foods (see Bourn and Prescott 2002; Yiridoe et al. 2005; Hughner et al. 2007, for example). Additionally, sustainable growers tend to utilize more direct-to-consumer marketing arrangements such as CSAs and farmers' markets to sell their produce (Martinez 2010) where traceability is likely high. These considerations suggest that sustainable growers may be less likely than conventional growers to invest in food safety practices, other than washing product to ensure its attractiveness to potential buyers.

Now combine the selection and expenditure models for each practice. Let I_{jk} be an indicator taking on a value of 1 if grower j uses practice k and a value of 0 if grower j does not use practice k. Normalize the variance of v_{jk} to 1 and let σ denote the variance of u_{jk} and ρ denote the correlation between u_{jk} and v_{jk}. The log likelihood function for a single food safety practice taking into account both non-use and non-reporting is:

$$
\begin{aligned}
&\log(L_k) = \\
&\sum_{j|I_{jk}=0} \log\Phi\left(-\left(\xi_k + \mu_k O_j + \sum_i \zeta_i T_{ji} + \theta_k \log(A_j)\right)\right) \\
&+ \sum_{j|I_{jk}=1,e_{jk}=0} \log\Phi\left(\xi_k + \mu_k O_j + \sum_i \zeta_i T_{ji} + \theta_k \log(A_j)\right) \\
&+ \sum_{j|I_{jk}=1,e_{jk}>0} \log\Phi\left(\frac{\xi_k + \mu_k O_j + \sum_i \zeta_i T_{ji} + \theta_k \log(A_j) + \frac{\rho}{\sigma}\left(\log(e_{jk}) - \beta_k - \sum_i \gamma_i T_{ji} - \eta_k \log(A_j)\right)}{\sqrt{1-\rho^2}}\right) \\
&+ \sum_{j|I_{jk}=1,e_{jk}>0} \log\left(\frac{1}{\sigma}\phi\left(\frac{\log(e_{jk}) - \beta_k - \sum_i \gamma_i T_{ji} - \eta_k \log(A_j)}{\sigma}\right)\right) \qquad (3.6)
\end{aligned}
$$

The first term in the log likelihood function is the probability that grower j does not use practice k, summed up over all growers not using practice k. The second term is the probability that grower j uses practice k, summed up over all growers using practice k but not reporting expenditures on practice k. The third term is the probability that grower j uses practice k conditional on grower j reporting positive expenditures on practice k, summed up over all growers reporting expenditures on practice k. The fourth term is the probability of observing reported expenditures $\log(e_{jk})$, summed up over all growers reporting expenditures on practice k. The third and fourth terms combined thus represent the unconditional probability of observing reported expenditures $\log(e_{jk})$ summed up over all growers reporting expenditures on practice k.

The model for groups of practices is analogous. We estimate two versions of the model for cases where total expenditures are reported for groups of practices. As presented in Equation 3.4, the main specification adds individual practices intercepts, $\sum_m (P_{jkm}\beta_{km})$, to the expenditure portion of the model; and it allows the acreage elasticities of each individual practice to vary by replacing $\eta_k \log(A_j)$ with $\log(A_j) \sum_m (P_{jkm}\eta_{km})$. A second specification uses only the group-level intercept β_k and assumes that the acreage elasticities of all practices within each group are the same, thus using $\eta_k \log(A_j)$, as presented in Equation 3.3. The specification of the selection equation is the same in both cases.

We estimate the parameters of these double hurdle models simultaneously for each practice or group of practices, i.e., our estimates are full information maximum likelihood estimates for each practice or group of practices.

3.6 Estimation Results

The elasticities of food safety practice expenditures, the impacts of sustainable production practices on food safety expenditures, and the marginal effects of factors influencing the probability of using a food safety practice, as estimated by maximum likelihood using the double hurdle model specified above, are reported in Tables 3.4, 3.5, and 3.6.[9] The number of observations used in each model varies because of differences in response rates for questions about the use of food safety practices (Table 3.4); missing observations for fruit and vegetable acreage A_j and the indicator for contractual obligations to use food safety practices O_j reduced the size of the usable sample by an additional 24-25 observations. The errors for sampling and testing, field inspection, container sanitation, and written records are positively correlated, underscoring the need for the double hurdle specification (Ap-

[9]Full sets of coefficient estimates for the double hurdle models without and with individual practice intercepts and interaction terms are presented in Appendix Tables C.2 and C.3, respectively.

pendix Table C.2). Because the probit selection model is nonlinear, we calculate average marginal effects for each of the regressors to help quantify the effect farm size, grower characteristics, and marketing channel have on the probability that growers use each safety measure (Table 3.6). The estimated marginal effects reported in Table 3.6 indicate that the contractual obligations indicator is a strong instrument for sampling and testing, field inspections, harvest container sanitation, written record keeping, and third party audits. Similarly, the share of output sold through wholesalers/repackers, mass merchandisers, exporters, brokers, or other outlets is a strong instrument for employee sanitation and hygiene practices. Only soil amendment treatment lacks a strong instrument for selection, likely because relatively few growers in our sample use soil amendments.

3.6.1 Effect of Farm Size on Expenditures on Food Safety Practices

There is concern that the Rule may adversely affect small produce growers and that compliance costs may be sufficiently burdensome to force many out of business, thereby increasing concentration in the industry. To better gauge this concern, we investigate how the expenditures and use of food safety practices vary with farm size. For each food safety practice, we use the estimated coefficient on the log of acreage (the elasticity of food safety expenditure for practice k with respect to acreage) to analyze how the expenditures for each food safety practice varies with farm size (Table 3.4). As noted earlier, inelastic expenditure on a food safety practice implies that larger operations spend less per acre than smaller ones, consistent with increasing returns to farm size; elastic expenditure implies that larger operations spend more per acre than smaller ones, consistent with decreasing returns to farm size; and unit elastic expenditure implies that expenditure per acre is constant, consistent with constant returns to farm size.

Consistent with previous studies of specific crops and geographic areas (Hardesty and Kusunose 2009; Ribera et al. 2012; Paggi et al. 2013; Driven to Discover 2012; Lichtenberg and Page 2016), the estimated coefficients for all but two of the food safety practices included in our survey data indicate that expenditures increase with operation size but less than proportionally.

In most cases, the estimated elasticities are not significantly different from zero, consistent with expenditures being fixed and thus decreasing in farm size. Additionally, likelihood ratio tests indicate that the estimated acreage elasticities of expenditure on soil samples ($\chi^2 = 28.72, p < 0.01$),[10] inspection for other causes ($\chi^2 = 38.41, p < 0.01$), new harvest containers ($\chi^2 = 101.4, p < 0.01$), employee education and training ($\chi^2 = 48.86, p < 0.01$), equipment and tool sanitation ($\chi^2 = 73.53, p < 0.01$), building sanitation ($\chi^2 = 79.90, p < 0.01$), sewage and trash disposal ($\chi^2 = 36.24, p < 0.01$), and other preventive measures ($\chi^2 = 40.61, p < 0.01$) are all significantly different from one, ruling out expenditures per acre proportional to farm size.

In several other cases, the estimated elasticities are less than one but significantly different from zero, ruling out expenditures independent of farm size. Like-

[10] Likelihood ratio tests for inspection for flooding and wildlife intrusion are each conducted on the sum of the individual flooding/wildlife intrusion and the simultaneous inspection for flooding and wildlife intrusion simultaneously.

lihood ratio tests indicate that the estimated elasticities of water samples ($\chi^2 = 35.42, p < 0.01$), washing harvest containers ($\chi^2 = 23.82, p < 0.01$), washing product ($\chi^2 = 19.60, p < 0.01$), keeping written records ($\chi^2 = 319.39, p < 0.01$), and third party audits ($\chi^2 = 39.58, p < 0.01$) are all significantly different from one as well as zero, consistent with expenditures per acre being variable but decreasing in farm size.

The estimated coefficients of the remaining food safety practices are somewhat mixed. Likelihood ratio tests indicate that the estimated elasticity of treating multiple soil amendments is not significantly different from one ($\chi^2 = 0.38, p = 0.54$) even though it is significantly different from zero, consistent with constant expenditures per acre. The estimated elasticities of inspection for wildlife intrusion ($\chi^2 = 0.16, p = 0.69$) and treating a single soil amendment ($\chi^2 = 0.31, p = 0.58$) are not significantly different from either zero or one. Both are close in magnitude to one, though (recall that the elasticity of inspection for wildlife intrusion is the sum of the wildlife intrusion and wildlife intrusion and flooding elasticities, 0.75), suggesting that expenditures on these two practices are also likely constant per acre.

3.6.2 Effect of Sustainable Farming Practices on Expenditures on Food Safety Practices

Sustainably grown food products, which are often sold locally through direct-to-consumer channels such as farmers' markets and community supported agriculture arrangements, account for a growing share of total U.S. agricultural sales (Martinez 2010). Between 2006 and 2014, the number of farmers' markets in the U.S. grew 180 percent, and local food sales totaled an estimated \$6.1 billion in 2012. Business survival also appears to be greater for farms selling into these markets (Low 2015).

Sustainable grower organizations have expressed concern that some provisions of the Produce Rule may be unduly burdensome to sustainable growers, particularly for the treatment of animal-based soil amendments. We use the estimated coefficient of the sustainable farming practices indicator to examine this possibility. The estimated coefficient of the sustainable indicator is positive for all food safety practices and significantly different from zero in the regressions for expenditures on harvest container sanitation, washing product, and keeping written records. All three indicate that sustainable growers spend as much as twice as much on these practices as conventional growers. However, it is by no means clear that greater expenditures on washing product and harvest container sanitation can be attributed to compliance with the Produce Rule, since they could easily be due to marketing considerations that predate the Produce Rule (e.g., delivering clean products in clean containers direct to consumers).

The estimated coefficients of the sustainable farming practices indicator in the equations for sampling and testing, field inspection, and written recordkeeping all suggest that sustainable grower spend 40-60% more on these practices than conventional growers. All of these coefficients except for that of written records are estimated imprecisely, however. Overall, then, the estimated coefficients of our econometric models provide limited evidence supporting the contention that compliance with the Produce Rule be more burdensome for sustainable growers than conventional ones.[11]

3.6.3 Effect of Farm Size and Sustainable Farming Practices on Use of Food Safety Practices

Lower costs should make larger farms more likely to invest in food safety. We find evidence supporting that hypothesis for some food safety practices. We find positive, statistically significant marginal effects of acreage on the probability of using sampling and testing, conducting field inspections, keeping written records, and having third-party audits. The effects of acreage on sampling and testing, field inspections, and third party audits are substantial: a 1 percent increase in acreage is associated with a 5-6 percentage point increase in the probability that each practice is used. The effect of acreage on written records is somewhat smaller but still substantial—a 1% increase in acreage is associated with a 2.5 percentage point increase in the probability of keeping written records. The estimated marginal effects for the remaining food safety practices are not statistically significantly different from zero and quite small in magnitude, implying that larger farms are no more or less likely than smaller operations to sanitize harvest containers, wash product, utilize employee sanitation and hygiene measures, or treat soil amendments.

We argued earlier that growers using sustainable farming practices might be

[11]For completeness, we investigate whether the elasticities of food safety practice expenditures with respect to acreage differed for conventional and sustainable grower. None of the coefficients of the interaction between the log of acreage and the sustainable grower indicator were significantly different from zero. All were small in magnitude as well.

less likely to invest in food safety measures since such investments would have low returns. Our econometric results provide another reason: higher costs of food safety measures. We find that sustainable growers are neither more nor less likely than conventional growers to employ most food safety measures. The exception is washing product: sustainable growers are 21 percentage points more likely to wash product, a result that is consistent with their heavier reliance on selling direct to consumers with whom they are likely to have personal ties. Overall, these estimates suggest that the Produce Rule will require changes in growing practices for similar shares of sustainable and conventional growers.

3.7 Policy Implications

Our estimates of the elasticities of food safety expenditures with respect to acreage indicate that per acre expenditures on most food safety practices decrease with farm size, suggesting that compliance with the Produce Rule will be more difficult for smaller operators than for larger ones. We examine the potential impacts of compliance with the Rule more closely by examining the cost burden of compliance. We define the cost burden of food safety practice k as expenditures on food safety practice k as a share of total production expenditures ${}^{e_k}/\left(\sum_j w_j X_j + \sum_n e_n\right)$. We investigate how that cost burden varies with (a) farm size and (b) the exemption thresholds using simulations based on our econometric estimates.

3.7.1 Farm Size and the Cost Burden

The elasticity of this cost burden with respect to acreage is $\psi_k = \eta_k - \lambda$, where λ denotes the elasticity of total expenditure with respect to acreage. We use our survey data to obtain an estimate of λ, which we obtain by regressing the log of total expenditures for fruit and vegetable production reported by each grower on the log of fruit and vegetable acreage. The estimate of λ obtained from this regression is 1.0049 (with a standard error of 0.0459, $R^2 = 0.66$ and $N = 244$) and the constant term is 8.3201 (with a standard error of 0.1450). Since the estimated elasticity is indistinguishable from one, we set $\lambda = 1$ in the simulations that follow in this section.

Overall, our results support the contention that the cost of compliance with the Produce Rule requirements will be more burdensome to small farms than large ones. The cost burden of food safety practices for which expenditures are fixed (invariant with respect to farm size) is inversely proportional to acreage. As we have seen, those practices include inspection for flooding, inspection for other causes, use of new harvest containers, employee education and training, equipment and tool sanitation, building sanitation, sewage and trash disposal, and other preventive sanitation measures. For each of these, a farm with ten times the acreage of a smaller farm will have a cost burden only a tenth the size that of the smaller farm. Similarly, the cost burden of food safety practices with acreage elasticities between zero and one will decline with farm size, albeit at a lower rate. The acreage elasticities of testing water samples and washing harvest containers, for instance, are about 0.55, implying an elasticity of the cost burden of -0.45 for each of these practices. The cost burden of these two practices for a farm with ten times the acreage of a smaller farm will be about 35% ($10^{-0.45}$) that of the smaller farm. Only in the cases of inspection for wildlife intrusion and testing soil amendments (either single or multiple) does the cost burden appear to be invariant with respect to farm size. Overall, then, our estimated coefficients indicate that that the Produce Rule will impose a much larger food safety cost burden on smaller operations than larger ones, consistent with the concerns raised by many small farm advocacy organizations.

3.7.2 Effect of Changes to FSMA Exemption Thresholds on Food Safety Cost Burden

The farm size and Tester-Hagan exemptions to FSMA are intended to protect very small and local food producers for whom the costs of complying with FSMA would be unduly burdensome. To better understand how growers at these exemption thresholds are affected by FSMA, we simulate how the magnitude of the food safety cost burden varies by farm revenue and share of direct sales. The former determines the size threshold for exemption while the two combined determine the Tester-Hagan exemption.

The cost burden of food safety practice k with our log-linear specification is $\exp(\alpha_k - \alpha_1)A^{(\eta_k - \lambda)}$; here α_1 is the constant term in the regression of log of total expenditures on log of acreage and α_k is the constant term in the expenditure equation for food safety practice k, which is different for each combination of crop type and farming practice. To conduct this simulation, we need to know how acreage varies with revenue and the share of direct sales. We use our survey data to obtain estimates of these two parameters by regressing the log of fruit and vegetable acreage on the log of fruit and vegetable revenue and the share of fruits and vegetables sold direct to consumers. Our estimate of the cost burden for a threshold combination of revenue R and share of direct sales s is: $\exp(\alpha_k - \alpha_1)\psi_0^{(\eta_k-\lambda)} R^{\psi_1(\eta_k-\lambda)} \exp(\psi_2(\eta_k - \lambda)s)$.[12] The coefficient of the log of revenue is $\psi_1 = 0.64$ (with a standard error of 0.0336). The coefficient of the share of direct sales is $\psi_2 = -0.0115$ (with a standard error of 0.002). The constant term is $\psi_0 = -3.9904$ (with a standard error of 0.4456). The regression uses 240 observations and has an $R^2 = 0.71$.

Table 3.7 presents our estimates of the cost burdens of each group of food safety practices for each combination of crop type and sustainable/conventional farming practices. To examine the impact of altering the thresholds for the Tester-Hagan exemption, we estimate cost burdens at the current levels ($500,000 in annual sales and 50% direct sales) and at combinations representing increases of 50% in each ($750,000 in annual sales and 75% direct sales). For the size exemption, we estimate cost burdens at the current level ($25,000 in annual sales) and at double that level ($50,000 in annual sales) assuming 49% direct sales in both cases. All estimates are presented as percentages (i.e., on a scale of 0-100).

Our simulation results suggest that even with significant economies of scale,

[12]For brevity, we limit our analysis to groups of practices (rather than individual practices within each group) using the acreage elasticities estimated with no interaction terms.

compliance with the Produce Rule would impose modest burdens on growers currently exempt from the Rule due to Tester-Hagan limits on size and share of direct sales. Expenditures on sampling and testing, field inspections, and keeping written records are each under 0.2% of total expenditures. Harvest container sanitation expenditures are larger but still under 0.75% of total expenditures. Washing vegetables requires the greatest expenditures but even this practice amounts to only 3.5 percent of total expenditures at the current exemption limits. Adding up the cost burden estimates of individual food safety practices for growers with the highest cost burdens (sustainable vegetable growers with annual sales of $500,000 selling 50% of output direct to consumers who treat soil amendments) gives an upper bound estimate of the impact of raising Tester-Hagan exemption thresholds. Doing so gives a total estimated cost burden of 10.5%. This figure is probably an overestimate, since most growers qualifying for the Tester-Hagan exemption wash product for marketing reasons already; deducting expenditures on washing product reduces the estimated cost burden to 7.0%. Such an increase in expenditures is quite modest. It could, however, correspond to a significant reduction in profit if margins are low.

While a large portion of small growers qualify for exemption from FSMA based on size or Tester-Hagan rules, small growers with revenue over $25,000 that do not sell at least 50% through direct marketing channels are not exempt from FSMA. The impact of raising the exemption threshold on those growers would be considerable. Consistent with the findings of Ribera et al. (2016), that impact is largely due to the high cost of third party audits, which amount to about 8.5% of total expenditures for sustainable berry growers with $25,000 in annual sales and almost 7.5% of total expenditures for conventional berry growers with $25,000 in annual sales. At the same time, however, the cost burdens of sampling and testing, field inspections, and keeping written records are quite low, all well under 0.5%, indicating that some of the food safety practices required under the Produce Rule could be extended to very small growers at acceptably low cost.

3.8 Conclusion

The passage of the Food Safety Modernization Act in 2011 authorized the FDA to regulate growing, harvesting, packing, and holding of fresh fruits and vegetables. The rule for produce safety, which became effective in January of 2016, sets standards for agricultural water, soil amendments of animal origin, domesticated and wild animals, employee health and hygiene, and equipment and building sanitation that could be costly for growers to implement. In particular, small farms worry that the costs of implementing the required food safety practices could put them out of business, and sustainable growers are afraid that the new standards could make it prohibitively expensive for them to maintain their current farming practices.

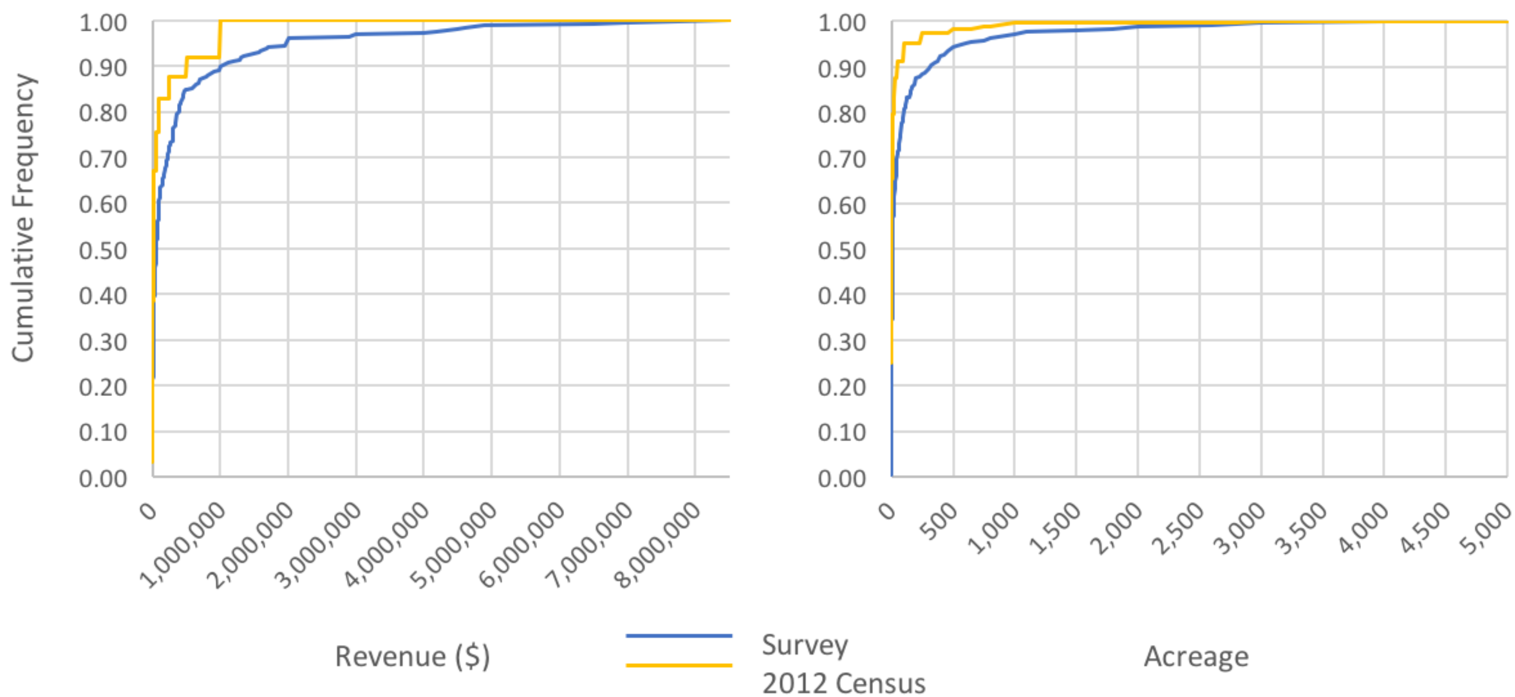
Data on the likely cost of the actions required under the new Rule is limited. We use data from a national survey of 394 fruit and vegetable growers to examine how expenditures on (and thus the cost burden of) food safety practices varies by farm size and farming practices. We estimate food safety practice expenditures as a function of acreage, whether sustainable growing practices were used, and other farm characteristics using a double hurdle model to control for selection in the use of each food safety practice and reporting expenditures on that practice. We find that expenditures on most food safety practices rise less than proportionally as farm size increases, implying that the cost burden of using them falls with farm size. Expenditures on many of these practices appear to be invariant with respect to farm size, implying that they fall in proportion to the inverse of acreage.

We also find evidence that sustainable growers spend substantially more on average on many of these practices than conventional growers, although our estimates are precise only for harvest container sanitation, washing product, and keeping written records. Recent years have seen growing consumer interest in local food markets, of which sustainable farming practices are an integral component (Thompson et al. 2008). While most sustainable growers in our sample are presently exempt from FSMA, our results suggest that the Produce Rule may pose barriers to expansion of sustainable farming. Our finding that sustainable growers spend more on average on food safety practices compared to conventional growers suggest these growers could face a considerable cost disadvantage upon surpassing the FSMA exemption threshold. While our simulations suggest that the magnitude of this burden is modest for most growers, the Produce Rule could limit the growth of some sustainable farming operations, making it desirable for them to stay below the exemption threshold. As the Produce Rule is phased in over the next three years, it will be important to keep an eye on its effect on sustainable growers and on the agricultural markets in which they participate.

We use our econometric results to conduct two simulation exercises examining how the cost burden of using these food safety practices varies with farm size. The first simulation exercise examines the ratio of food safety expenditures to total production expenditures, which we define as the cost burden. We find that this cost burden falls substantially with farm size: For most food safety practices, increasing farm size by a factor of ten decreases this cost burden by 45-90%. The second simulation exercise estimates the cost burden for farms that are currently exempt due to size in terms annual sales or due to the Tester-Hagan amendment, which exempts farms using a combination of annual sales and share of sales direct to consumers. This exercise shows that raising exemption thresholds would impose a relatively small cost burden on farms that are currently exempt by the Tester-Hagan amendment. For farms that are exempt by size class, raising the threshold for exemption would impose modest increases in cost for most practices, the exception being third party audit. We thus find little or no evidence that compliance with the Produce Rule will threaten the competitiveness of small operations to any significant extent.

A caveat to the inferences drawn here comes from the nature of our data. Our sample is broadly representative of commercial produce growers in most of the U.S. but underrepresents commercial produce growers in California, Arizona, Texas, and Florida, the states that account for the largest shares of fruit and vegetable production. Growers in these underrepresented states operate largely under contracts with packing firms, marketing firms, and grocery chains; those contracts often mandate the use of many of the food safety practices considered here. Food safety practice usage rates and expenditures by growers in these states may thus differ from those of growers elsewhere in the U.S. Our sample is broadly representative of the population of fruit and vegetable growers in the U.S., so that our analysis yields reasonable inferences about the likely effects of the Produce Rule on growers. But our sample underrepresents fruit and vegetable production and thus cannot be used to draw inferences about effects of the Produce Rule on fruit and vegetable markets (i.e., output and price levels).

Figure 3.1: Empirical Distributions of Fruit and Vegetable Farm Revenue and Farm Acreage



Source: 2012 USDA Census of Agriculture national vegetable totals

Note: 140 respondents (36%) chose not to report revenue, and 29 respondents (7%) chose not to report acreage.

Table 3.1: Survey Descriptive Statistics

Variable	Listserv Average	Conference Average	Total Observations
Number of Observations	277	117	394
Use of Food Safety Practices (Share of Subsample)			
Sampling and Testing	0.38	0.5	328
Field Inspections	0.36	0.44	318
Harvest Container Sanitation	0.67	0.76	321
Wash Product	0.54	0.59	317
Employee Sanitation and Hygiene	0.66	0.84	313
Written Records	0.56	0.69	309
Soil Amendment Treatment	0.3	0.2	169
Third Party Audits	0.14	0.24	303
Crop Type (Share of Subsample)			
Berries Only	0.03	0.07	394
Fruit and Tree Nuts Only	0.17	0.09	394
Vegetables Only	0.25	0.37	394
Fruit/Tree Nuts and Berries	0.03	0.01	394
Vegetables and Berries	0.16	0.23	394
Vegetables and Fruit/Tree Nuts	0.09	0.06	394
Berries, Fruit/Tree Nuts, and Vegetables	0.27	0.18	394
Farming Practices (Share of Subsample)			
Sustainable	0.44	0.07	394
Conventional	0.56	0.93	394
Share of Output Sold through Marketing Channel (%)			
Direct Sale	62.18	53.85	338
Wholesale/Mass Merchandiser / Exporter / Broker / Shipper / Other	28.14	30.28	338
Grocery Retailers	6.69	13.3	338
Foodservice Operations	3.63	3.05	338
Other Explanatory Variables			
Contractual Obligation (Share of Subsample)	0.23	0.37	326
Log Fruit and Vegetable Acreage	2.14	3.85	365
Log Fruit and Vegetable Expenditures	10.42	11.47	253
Log Fruit and Vegetable Revenue	10.84	11.85	254

Table 3.2: Regional Distributions of Farm Operations

U.S. Region	U.S. Census of Agriculture (%)	Sample (%)
Vegetables	72045	287
Midwest	23.9	25.8
Northeast	19.6	27.9
South	29.8	37.3
West	26.8	9.1
Berries	30538	181
Midwest	22.1	19.9
Northeast	25.5	27.6
South	31.6	42
West	20.8	10.5
Fruit and Tree Nuts	31126	181
Midwest	3.2	21
Northeast	0.7	25.4
South	44.6	28.7
West	51.5	24.9

Source: 2012 USDA Census of Agriculture - Vegetable Operations

Note: 5 respondents (1%) chose not to report state

Table 3.3: Exemption Status by Farm Size and Grower Organization

Classification	Size Exempt	Tester-Hagan Exempt	Grand Total Exempt
Economic Class			
Exempt ($25,000 or less)	91 (100%)	-	91
Very Small ($25,001 to $250,000)	-	80 (93%)	80
Small ($250,001 to $500,000)	-	24 (75%)	24
Medium/Large (More than $500,000)	-	-	-
Grower Organization			
Conventional	42 (27%)	60 (38%)	102 (65%)
Sustainable	49 (51%)	44 (45%)	93 (96%)
TOTAL	91 (36%)	104 (41%)	195 (77%)

Note: 140 respondents (36%) chose not to report revenue, so exemption status cannot be determined.

Table 3.4: Estimated Farm Size Elasticities of Food Safety Practice Expenditures

Dependent variable = log expenditures	With Interactions	No Interaction
Panel A. Sampling and Testing (N = 303)		
Log Fruit and Veg. Acreage x Water Samples	0.5510*** (0.0754)	-
Log Fruit and Veg. Acreage x Soil Amendment Samples	0.2094 (0.1475)	-
Log Fruit and Veg. Acreage x Product Samples	0.0604 (0.1126)	-
Log Fruit and Veg. Acreage	-	0.6955*** (0.0764)
Panel B. Field Inspection (N = 294)		
Log Fruit and Veg. Acreage x Flooding	-0.2032 (0.6088)	-
Log Fruit and Veg. Acreage x Wildlife Intrusion	0.5097*** (0.1049)	-
Log Fruit and Veg. Acreage x Other Causes	0.1554 (0.1363)	-
Log Fruit and Veg. Acreage x Flooding x Wildlife Intrusion	0.2448 (0.6166)	-
Log Fruit and Veg. Acreage	-	0.5608*** (0.0795)
Panel C. Harvest Container Sanitation (N = 297)		
Log Fruit and Veg. Acreage x Wash Containers	-0.0291 (0.1022)	-
Log Fruit and Veg. Acreage x New Containers	0.5607*** (0.0900)	-
Log Fruit and Veg. Acreage	-	0.5475*** (0.0602)
Panel D. Washing Product (N = 294)		
Log Fruit and Veg. Acreage	-	0.6816*** (0.0719)
Panel E. Employee Sanitation and Hygiene (N = 290)		
Log Fruit and Veg. Acreage x Employee Training	0.0877 (0.1305)	-

Continued...

Table 3.4 – continued from previous page

Dependent variable = log expenditures	With Interactions	No Interaction
Log Fruit and Veg. Acreage x Toilet/Handwash Facilities	-0.1345	-
	(0.1323)	
Log Fruit and Veg. Acreage x Equipment Sanitation	0.0337	-
	-0.1081)	
Log Fruit and Veg. Acreage x Building Sanitation	0.6863***	-
	-0.2062)	
Log Fruit and Veg. Acreage x Sewage/Trash Disposal	-0.1469	-
	(0.1905)	
Log Fruit and Veg. Acreage x Other Preventive Actions	0.117	-
	(0.1386)	
Log Fruit and Veg. Acreage	-	0.6319***
		(0.0542)
Panel F. Written Records (N = 296)		
Log Fruit and Veg. Acreage	-	0.2560***
		(0.0416)
Panel G. Soil Amendment Treatment (N = 169)		
Log Fruit and Veg. Acreage x Single Soil Amendment	1.5959	-
	(1.078)	
Log Fruit and Veg. Acreage x Multiple Soil Amendments	0.8995***	-
	(0.1626)	
Log Fruit and Veg. Acreage	-	0.9180***
		(0.1587)
Panel H. Third Party Audit (N = 283)		
Log Fruit and Veg. Acreage	-	0.3798***
		(0.0986)

Note: Each regression is estimated by maximum likelihood using a double hurdle specification. All regressions contain crop type (vegetables, berries, fruit and tree nuts) and an indicator for sustainable farming practices as controls. Interaction models for groups of practices also contain indicators for each type of practice within the group as controls. Standard errors are reported in parentheses. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10, 5 and 1 percent level, respectively.

Table 3.5: Estimated Impact of Sustainable Farming Practices on Food Safety Practice Expenditures

Practice Type	With Interactions	No Interaction
Sampling and Testing	0.4900	0.4638
	(0.3559)	(0.3922)
Field Inspection	0.4125	0.4685
	(0.3652)	(0.3754)
Harvest Container Sanitation	0.6788***	0.6253**
	(0.2477)	(0.2448)
Washing Product	-	0.7333**
		(0.3231)
Employee Sanitation	0.1592	0.2675
	(0.2416)	(0.2482)
Written Records	-	0.4459**
		(0.1954)
Soil Amendment Treatment	0.2349	0.2322
	(0.3965)	(0.3848)
Third Party Audit	-	0.1249
		(0.5112)

Note: Each regression is estimated by maximum likelihood using a double hurdle specification. All regressions contain crop type (vegetables, berries, fruit and tree nuts) as controls. Interaction models for groups of practices also contain indicators for each type of practice within the group as controls. Standard errors are reported in parentheses. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10, 5 and 1 percent level, respectively.

Table 3.6: Marginal Effects of Acreage, Marketing Channel, Farming Practices, and Crop Type on the Probability of Safety Measure Use

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Washing Product	Employee Sanitation & Hygiene	Written Records	Soil Amendment Treatment	Third-Party Audits
Log Fruit and Vegetable Acreage	0.0649***	0.0520***	-0.0119	-0.0102	0.0107	0.0254*	-0.0238	0.0455***
	(0.0146)	(0.0148)	(0.0088)	(0.0126)	(0.0096)	(0.0135)	(0.0234)	(0.0094)
Contractual Obligation	0.1543**	0.2517***	0.0779*	-0.0288	0.0276	0.3197***	0.1339	0.2141***
	(0.0749)	(0.0674)	(0.0444)	(0.0607)	(0.0493)	(0.1077)	(0.1318)	(0.0287)
Wholesale / Other Sale Share	0.0007	-0.0007	-0.0003	0.001	-0.0011**	0.0000	-0.0021	0.0001
	(0.0008)	(0.0008)	(0.0004)	(0.0007)	(0.0006)	(0.0007)	(0.0014)	(0.0005)
Sustainable	0.0304	-0.0678	0.0071	0.2129***	0.0263	0.03	0.0217	-0.0479
	(0.0601)	(0.0638)	(0.0393)	(0.0603)	(0.0401)	(0.0471)	(0.0824)	(0.0503)
Berries	-0.0234	-0.0433	0.0993***	0.0347	0.0711*	-0.0162	-0.0353	-0.0341
	(0.0518)	(0.0556)	(0.0368)	(0.0473)	(0.0365)	(0.0414)	(0.0798)	(0.0354)
Fruit and Tree Nut	0.0462	-0.0098	-0.0181	0.0651	-0.0566	0.0531	0.0234	-0.0134
	(0.0541)	(0.0585)	(0.037)	(0.051)	(0.0375)	(0.0452)	(0.0804)	(0.0387)
Vegetables	-0.1097	0.1421*	-0.0205	0.3123***	-0.1508**	0.0495	-0.0532	-0.0557
	(0.0752)	(0.0807)	(0.0478)	(0.0554)	(0.0619)	(0.062)	(0.2069)	(0.0458)

Note: Each regression is estimated by maximum likelihood using a double hurdle specification. All regressions contain crop type (vegetables, berries, fruit and tree nuts) and an indicator for sustainable farming practices as controls. Models for groups of practices also contain indicators for each type of practice within the group as controls. Standard errors (reported in parentheses) were estimated using the delta method. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10, 5 and 1 percent level, respectively.

Table 3.7: Effects of Changes to Exemption Thresholds on Food Safety Cost Burden Percentage for Each Food Safety Practice

A. Change to Tester-Hagan Exemption Revenue Threshold (Direct Sales Share = 50%)					
	Farming Practices	Sustainable		Conventional	
	Revenue	$500,000	$750,000	$500,000	$750,000
Sampling and Testing	Berries	0.1709	0.1577	0.1075	0.0992
	Fruit and Tree Nuts	0.1149	0.1061	0.0723	0.0667
	Vegetables	0.0981	0.0905	0.0617	0.0569
Field Inspection	Berries	0.1205	0.1074	0.0754	0.0672
	Fruit and Tree Nuts	0.1997	0.1779	0.125	0.1114
	Vegetables	0.1868	0.1664	0.1169	0.1042
Harvest Container Sanitation	Berries	0.7155	0.6354	0.3829	0.34
	Fruit and Tree Nuts	0.5367	0.4766	0.2872	0.255
	Vegetables	0.7848	0.697	0.4199	0.3729
Washing Product	Berries	1.5824	1.455	0.76	0.6988
	Fruit and Tree Nuts	2.6088	2.3988	1.253	1.1522
	Vegetables	3.5089	3.2265	1.6853	1.5497
Employee Sanitation and Hygiene	Berries	1.023	0.9286	0.7829	0.7106
	Fruit and Tree Nuts	1.1086	1.0063	0.8484	0.7701
	Vegetables	1.1754	1.0669	0.8995	0.8165
Written Records	Berries	0.0048	0.0039	0.003	0.0025
	Fruit and Tree Nuts	0.0032	0.0026	0.0021	0.0017
	Vegetables	0.0033	0.0028	0.0021	0.0018
Soil Amendment Treatment	Berries	1.4652	1.4325	1.1615	1.1356
	Fruit and Tree Nuts	1.956	1.9123	1.5506	1.516
	Vegetables	2.7608	2.6992	2.1886	2.1398
Third Party Audit	Berries	2.572	2.1869	2.2701	1.9302
	Fruit and Tree Nuts	0.8542	0.7263	0.7539	0.641
	Vegetables	1.0672	0.9074	0.9419	0.8009
B. Change to Tester-Hagan Exemption Direct Sales Share Threshold (Revenue = $500,000)					
	Farming Practices	Sustainable		Conventional	
	Direct Sales Share	50%	75%	50%	75%
Sampling and Testing	Berries	0.1709	0.1868	0.1075	0.1175
	Fruit and Tree Nuts	0.1149	0.1257	0.0723	0.079
	Vegetables	0.0981	0.1072	0.0617	0.0674

Continued...

Table 3.7 – continued from previous page

Field Inspection	Berries	0.1205	0.137	0.0754	0.0857
	Fruit and Tree Nuts	0.1997	0.2269	0.125	0.142
	Vegetables	0.1868	0.2122	0.1169	0.1328
Harvest Container Sanitation	Berries	0.7155	0.8162	0.3829	0.4367
	Fruit and Tree Nuts	0.5367	0.6122	0.2872	0.3276
	Vegetables	0.7848	0.8952	0.4199	0.479
Washing Product	Berries	1.5824	1.7367	0.76	0.8341
	Fruit and Tree Nuts	2.6088	2.8632	1.253	1.3752
	Vegetables	3.5089	3.8511	1.6853	1.8497
Employee Sanitation and Hygiene	Berries	1.023	1.1389	0.7829	0.8716
	Fruit and Tree Nuts	1.1086	1.2342	0.8484	0.9445
	Vegetables	1.1754	1.3086	0.8995	1.0014
Written Records	Berries	0.0048	0.0059	0.003	0.0038
	Fruit and Tree Nuts	0.0032	0.004	0.0021	0.0025
	Vegetables	0.0033	0.0042	0.0021	0.0027
Soil Amendment Treatment	Berries	1.4652	1.5023	1.1615	1.1909
	Fruit and Tree Nuts	1.956	2.0055	1.5506	1.5899
	Vegetables	2.7608	2.8307	2.1886	2.2441
Third Party Audit	Berries	2.572	3.0789	2.2701	2.7175
	Fruit and Tree Nuts	0.8542	1.0225	0.7539	0.9025
	Vegetables	1.0672	1.2775	0.9419	1.1275
C. Change to FSMA Revenue Exemption Threshold (Direct Sales Share = 49%)					
	Farming Practices	Sustainable		Conventional	
	Revenue	\$25,000	\$50,000	\$25,000	\$50,000
Sampling and Testing	Berries	0.3082	0.2687	0.1938	0.169
	Fruit and Tree Nuts	0.2073	0.1807	0.1304	0.1136
	Vegetables	0.1769	0.1542	0.1113	0.097
Field Inspection	Berries	0.281	0.2307	0.1759	0.1444
	Fruit and Tree Nuts	0.4655	0.3822	0.2914	0.2393
	Vegetables	0.4354	0.3575	0.2725	0.2238
Harvest Container Sanitation	Berries	1.7108	1.3966	0.9155	0.7473
	Fruit and Tree Nuts	1.2833	1.0476	0.6867	0.5606
	Vegetables	1.8764	1.5318	1.0041	0.8197
Washing Product	Berries	2.9304	2.5388	1.4075	1.2194
	Fruit and Tree Nuts	4.8313	4.1857	2.3205	2.0104
	Vegetables	6.4982	5.6298	3.1211	2.704

Continued...

Table 3.7 – continued from previous page

Employee Sanitation and Hygiene	Berries	2.0825	1.7649	1.5938	1.3507
	Fruit and Tree Nuts	2.2568	1.9126	1.7271	1.4637
	Vegetables	2.3928	2.0279	1.8312	1.5519
Written Records	Berries	0.0198	0.0142	0.0127	0.0091
	Fruit and Tree Nuts	0.0134	0.0096	0.0086	0.0061
	Vegetables	0.0139	0.01	0.0089	0.0064
Soil Amendment Treatment	Berries	1.7292	1.6637	1.3708	1.3189
	Fruit and Tree Nuts	2.3084	2.2211	1.83	1.7608
	Vegetables	3.2583	3.135	2.583	2.4853
Third Party Audit	Berries	8.4646	6.4148	7.4711	5.6619
	Fruit and Tree Nuts	2.8112	2.1304	2.4812	1.8804
	Vegetables	3.5121	2.6616	3.0999	2.3492

Note: Food safety cost burdens are expressed in percentage terms.

Appendix A: Appendix to Chapter 1

A.1 Solution for the Baseline Equilibrium

In the baseline equilibrium, Firm A solves the profit maximization problem

$$\Pi_A^* = \max_{q_{iA}, p_{iA}} N_H x_H \left(p_{HA} - \frac{\gamma q_{HA}^2}{2} \right) + N_L x_L \left(p_{LA} - \frac{\gamma q_{LA}^2}{2} \right),$$

and Firm B solves the profit maximization problem

$$\Pi_B^* = \max_{q_{iB}, p_{iB}} N_H (1 - x_H) \left(p_{HB} - \frac{\gamma q_{HB}^2}{2} \right) + N_L (1 - x_L) \left(p_{LB} - \frac{\gamma q_{LB}^2}{2} \right),$$

where x_i takes the form specified in Equation 1.1. By solving the first order conditions for the above problems, we obtain the equilibrium prices and qualities in Equation 1.2 and firm profits are

$$\Pi_A^* = \frac{1}{18} \left(N_H k_H (2 + a_H + b_H)^2 + N_L k_L (2 + a_L + b_L)^2 \right)$$
$$\Pi_B^* = \frac{1}{18} \left(N_H k_H (-4 + a_H + b_H)^2 + N_L k_L (-4 + a_L + b_L)^2 \right)$$

A.2 Solution When Only Firm A Labels Products

If only Firm A chooses to obtain the non-GMO label, the new location x_i of the consumer in segment i indifferent between buying products of quality q_{iA} and q_{iB} offered by each firm is

$$x_i = \frac{\theta_i(q_{iA} - q_{iB}) + k_i(a_i + b_i) - (p_{iA} - p_{iB}) + \delta_i}{2k_i} \quad \text{if} \quad a_i \leq x_i \leq b_i, \tag{A.1}$$

and the respective profit maximization problems that each firm solves are

$$\begin{aligned}
\Pi_A^* &= \max_{p_{iA}} N_H x_H \left(p_{HA} - \frac{\gamma q_{HA}^2}{2} - \alpha \right) + N_L x_L \left(p_{LA} - \frac{\gamma q_{LA}^2}{2} - \alpha \right), \\
\Pi_B^* &= \max_{p_{iB}} N_H (1 - x_H) \left(p_{HB} - \frac{\gamma q_{HB}^2}{2} \right) + N_L (1 - x_L) \left(p_{LB} - \frac{\gamma q_{LB}^2}{2} \right).
\end{aligned}$$

By solving the first order conditions for the new prices and substituting in the equilibrium qualities from the baseline case, the new optimal prices are

$$\begin{aligned}
p_{iA}^* &= \frac{1}{6} \left(2k_i(2 + a_i + b_i) + 4\alpha + 2\delta_i \right) + \frac{\theta_i^2}{2\gamma}, \\
p_{iB}^* &= \frac{1}{6} \left(2k_i(4 - a_i - b_i) + 2\alpha - 2\delta_i \right) + \frac{\theta_i^2}{2\gamma}.
\end{aligned}$$

From this result, it follows that Firm A captures additional market share and commands higher price-cost margins than Firm B, provided that $\delta_i > \alpha$. Furthermore, Firm B's profit decreases relative to the baseline case prior to labeling.

A.3 Equilibrium When Both Firms Labels Products

If both firms chooses to obtain the non-GMO label, the indifference location x_i once again takes the form specified in Equation 1.1, and the respective profit maximization problems that each firm solves are

$$\Pi_A^* = \max_{p_{iA}} N_H x_H \left(p_{HA} - \frac{\gamma q_{HA}^2}{2} - \alpha \right) + N_L x_L \left(p_{LA} - \frac{\gamma q_{LA}^2}{2} - \alpha \right),$$
$$\Pi_B^* = \max_{p_{iB}} N_H (1 - x_H) \left(p_{HB} - \frac{\gamma q_{HB}^2}{2} - \alpha \right) + N_L (1 - x_L) \left(p_{LB} - \frac{\gamma q_{LB}^2}{2} - \alpha \right).$$

By solving the first order conditions for the new prices and substituting in the equilibrium qualities from the baseline case, the new optimal prices are

$$p_{iA}^* = \frac{1}{6} \left(2k_i (2 + a_i + b_i) \right) + \frac{\theta_i^2}{2\gamma} + \alpha,$$
$$p_{iB}^* = \frac{1}{6} \left(2k_i (4 - a_i - b_i) \right) + \frac{\theta_i^2}{2\gamma} + \alpha.$$

It is now trivial to show that neither firm gains any market share nor increases their profits above the baseline equilibrium.

A.4 Equilibrium When Firms Develop New Products

In this scenario, when both market segments are fully served, the location x_H of the consumer in segment H indifferent between buying products of quality q_{HA}

and q_{HB} offered by each firm is

$$x_H = \frac{\theta_H(1+\delta_H)(q_{HA}-q_{HB}) + k_H(1+\delta_H)(a_H+b_H) - (p_{HA}-p_{HB})}{2k_H(1+\delta_H)}.$$

The location x_L is given by Equation 1.1. Firm A solves the profit maximization problem

$$\Pi_A^* = \max_{q_{HA},p_{iA}} N_H x_H \left(p_{HA} - \frac{\gamma q_{HA}^2}{2} - \alpha \right) + N_L x_L \left(p_{LA} - \frac{\gamma q_{LA}^2}{2} - \alpha \right),$$

and Firm B solves the profit maximization problem

$$\Pi_B^* = \max_{q_{HB},p_{iB}} N_H (1-x_H) \left(p_{HB} - \frac{\gamma q_{HB}^2}{2} - \alpha \right) + N_L (1-x_L) \left(p_{LB} - \frac{\gamma q_{LB}^2}{2} - \alpha \right),$$

By solving the first order conditions for the above problems, we obtain the equilibrium prices and qualities in Equation 1.3 and firm profits are

$$\Pi_A^* = \frac{1}{18}\left(N_H k_H (1+\delta_H)(2+a_H+b_H)^2 + N_L k_L (2+a_L+b_L)^2 \right)$$
$$\Pi_B^* = \frac{1}{18}\left(N_H k_H (1+\delta_H)(-4+a_H+b_H)^2 + N_L k_L (-4+a_L+b_L)^2 \right).$$

A.5 Price Premium Estimation with Full Sample

As a robustness check, the regression specification in Equation 1.5 was estimated using an unrestricted sample of Nielsen data spanning 2009 to 2014. In addition to the observations included in the restricted sample, this sample includes products that were non-GMO certified with *less than* 6 months of sales data prior to being certified and/or 12 months of sales after certification, and products that never obtained non-GMO certification. Table A.1 presents results from this sample with a progression of fixed effects identical to those presented in the main paper. Across all three specifications, the coefficient estimates for the post-certification treatment indicators are very small and not statistically significantly different from zero, consistent with the results presented in the main paper using the restricted sample.

Table A.1: Price Premium Regressions - Unrestricted Sample

	I	II	III
Pre-Cert. 6-12 Mos.	-0.007^{*}	-0.005	-0.006
	(0.003)	(0.004)	(0.005)
Pre-Cert. 0-6 Mos.	-0.002	0.001	0.000
	(0.003)	(0.005)	(0.006)
Post-Cert. 0-6 Mos	-0.002	-0.001	0.001
	(0.004)	(0.007)	(0.007)
Post-Cert. 6-12 Mos.	-0.001	-0.007	-0.003
	(0.004)	(0.007)	(0.008)
Post-Cert. 12-24 Mos.	-0.005	-0.009	-0.002
	(0.004)	(0.008)	(0.009)
Post-Cert. 24+ Mos.	0.007	0.000	0.012
	(0.005)	(0.011)	(0.012)
UPC FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
× Category	Yes	No	Yes
× Manufacturer	No	Yes	Yes
Adj. R^2	0.969	0.973	0.973
Num. obs.	10366743	10366743	10366743

Note: Each column represents a separate regression. Standard errors are clustered at the product level in parentheses: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Appendix B: Appendix to Chapter 2

B.1 Additional Tables

Tables B.1, B.2, B.3, B.4, and B.5 present median own- and cross-price elasticities for each of the 50 RTE cereal brands, across all 5,988 markets.

Table B.1: Median Own- and Cross-Price Elasticities - Brands 1-10

Brand	1	2	3	4	5	6	7	8	9	10
1	4.131	-0.002	-0.000	-0.000	-0.000	-0.001	-0.000	-0.001	-0.019	-0.000
2	-0.000	-3.341	0.159	0.035	0.015	0.268	0.017	0.118	0.022	0.056
3	-0.000	0.189	-3.792	0.043	0.017	0.326	0.020	0.142	0.029	0.066
4	-0.000	0.166	0.165	-3.573	0.015	0.279	0.017	0.123	0.023	0.057
5	-0.000	0.144	0.138	0.031	-3.153	0.239	0.015	0.103	0.017	0.048
6	-0.000	0.185	0.186	0.042	0.017	-3.583	0.019	0.140	0.028	0.064
7	-0.000	0.154	0.152	0.034	0.014	0.256	-3.403	0.112	0.018	0.052
8	-0.000	0.165	0.164	0.037	0.015	0.282	0.017	-3.450	0.024	0.057
9	-0.000	0.052	0.057	0.012	0.004	0.097	0.005	0.040	-1.173	0.020
10	-0.000	0.190	0.189	0.043	0.017	0.319	0.020	0.140	0.028	-3.911
11	-0.000	0.106	0.105	0.024	0.010	0.175	0.011	0.076	0.005	0.036
12	0.000	0.003	0.003	0.001	0.000	0.005	0.000	0.002	0.000	0.001
13	0.000	0.007	0.008	0.002	0.001	0.013	0.001	0.006	0.001	0.003
14	-0.000	0.119	0.114	0.026	0.011	0.194	0.012	0.084	0.008	0.041
15	-0.000	0.109	0.110	0.024	0.010	0.186	0.009	0.077	0.003	0.039
16	-0.000	0.117	0.118	0.025	0.010	0.198	0.010	0.081	0.004	0.040
17	-0.000	0.080	0.076	0.018	0.007	0.131	0.007	0.057	-0.005	0.028
18	0.000	0.014	0.019	0.003	0.001	0.030	0.001	0.011	0.001	0.006
19	-0.000	0.077	0.104	0.018	0.006	0.155	0.005	0.056	0.002	0.029
20	-0.000	0.128	0.135	0.026	0.014	0.210	0.006	0.088	0.005	0.040
21	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
22	-0.000	0.148	0.150	0.033	0.014	0.254	0.016	0.112	0.018	0.053
23	-0.000	0.201	0.203	0.045	0.018	0.342	0.021	0.147	0.029	0.071
24	-0.000	0.155	0.154	0.035	0.014	0.261	0.016	0.115	0.019	0.054
25	0.000	0.221	0.231	0.050	0.020	0.381	0.023	0.163	0.032	0.080
26	0.000	0.237	0.249	0.054	0.021	0.415	0.024	0.175	0.034	0.087
27	-0.000	0.194	0.195	0.044	0.018	0.326	0.020	0.143	0.029	0.069
28	0.000	0.250	0.277	0.059	0.022	0.456	0.025	0.189	0.032	0.096
29	0.000	0.231	0.238	0.052	0.020	0.398	0.024	0.169	0.033	0.084
30	-0.000	0.139	0.134	0.030	0.013	0.226	0.014	0.100	0.015	0.047
31	-0.000	0.120	0.113	0.026	0.011	0.193	0.012	0.085	0.009	0.041
32	-0.000	0.100	0.099	0.022	0.009	0.165	0.010	0.070	0.002	0.035
33	-0.000	0.142	0.137	0.031	0.013	0.230	0.014	0.101	0.015	0.048
34	0.000	0.252	0.287	0.059	0.021	0.468	0.025	0.193	0.030	0.099
35	0.000	0.281	0.278	0.062	0.021	0.486	0.030	0.208	0.033	0.114
36	-0.000	0.001	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.000
37	-0.000	0.001	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.000
38	0.000	0.001	0.001	0.000	0.000	0.002	0.000	0.001	0.000	0.000
39	0.000	0.212	0.242	0.047	0.018	0.395	0.019	0.154	0.024	0.080
40	-0.000	0.215	0.217	0.048	0.019	0.365	0.022	0.158	0.031	0.077
41	0.000	0.255	0.288	0.060	0.022	0.471	0.025	0.193	0.031	0.100
42	-0.000	0.181	0.178	0.040	0.017	0.300	0.019	0.130	0.026	0.062
43	-0.000	0.183	0.182	0.039	0.016	0.306	0.018	0.127	0.022	0.063
44	-0.000	0.189	0.195	0.040	0.017	0.321	0.018	0.132	0.023	0.066
45	0.000	0.216	0.223	0.049	0.019	0.369	0.022	0.160	0.031	0.077
46	0.000	0.220	0.227	0.050	0.020	0.374	0.023	0.161	0.032	0.079
47	-0.000	0.180	0.179	0.040	0.016	0.304	0.018	0.130	0.025	0.063
48	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.002	0.002	0.000	0.000	0.003	0.000	0.001	0.000	0.001
50	0.000	0.003	0.003	0.001	0.000	0.005	0.000	0.002	0.000	0.001

Note: Each cell entry in row i, column j represents the median elasticity of the market share of brand i with respect to the price of brand j, over all 5,988 markets.

Table B.2: Median Own- and Cross-Price Elasticities - Brands 11-20

Brand	11	12	13	14	15	16	17	18	19	20
1	-0.002	0.000	0.000	-0.001	-0.003	-0.005	-0.004	0.000	-0.000	-0.004
2	0.017	0.000	0.000	0.010	0.010	0.023	0.010	0.000	0.003	0.007
3	0.019	0.000	0.001	0.011	0.014	0.029	0.013	0.000	0.005	0.011
4	0.017	0.000	0.000	0.010	0.011	0.024	0.011	0.000	0.003	0.008
5	0.015	0.000	0.000	0.008	0.009	0.019	0.009	0.000	0.001	0.006
6	0.019	0.000	0.001	0.011	0.013	0.027	0.012	0.000	0.004	0.009
7	0.016	0.000	0.000	0.009	0.010	0.022	0.010	0.000	0.003	0.008
8	0.017	0.000	0.000	0.010	0.011	0.023	0.010	0.000	0.003	0.008
9	0.002	0.000	0.000	0.002	0.001	0.002	-0.002	0.000	0.000	0.001
10	0.019	0.000	0.001	0.011	0.014	0.028	0.013	0.000	0.004	0.009
11	-2.446	0.000	0.000	0.006	0.006	0.012	0.005	0.000	0.001	0.004
12	0.000	-3.424	0.061	0.000	0.001	0.002	0.000	0.018	0.001	0.005
13	0.001	0.030	-3.442	0.000	0.004	0.006	0.000	0.010	0.007	0.005
14	0.011	0.000	0.000	-2.718	0.008	0.016	0.007	0.000	0.001	0.005
15	0.009	0.000	0.002	0.006	-3.170	0.032	0.004	0.001	0.002	0.006
16	0.009	0.000	0.002	0.007	0.017	-3.255	0.005	0.001	0.002	0.007
17	0.006	0.000	0.000	0.004	0.003	0.007	-1.773	0.000	0.000	0.002
18	0.001	0.033	0.036	0.001	0.004	0.009	0.000	-3.272	0.007	0.009
19	0.005	0.025	0.022	0.003	0.005	0.015	0.002	0.005	-3.404	0.010
20	0.009	0.031	0.042	0.006	0.007	0.028	0.005	0.002	0.007	-3.084
21	0.000	0.007	0.003	0.000	0.000	0.000	0.000	0.000	-0.000	-0.004
22	0.016	0.000	0.000	0.009	0.010	0.021	0.009	0.000	0.003	0.008
23	0.021	0.000	0.001	0.012	0.015	0.030	0.013	0.000	0.005	0.011
24	0.016	0.000	0.000	0.009	0.010	0.022	0.009	0.000	0.003	0.008
25	0.022	0.000	0.001	0.013	0.017	0.034	0.014	0.001	0.006	0.013
26	0.022	0.000	0.001	0.014	0.018	0.037	0.015	0.001	0.006	0.013
27	0.020	0.000	0.001	0.012	0.014	0.029	0.013	0.000	0.004	0.010
28	0.022	0.000	0.001	0.014	0.019	0.039	0.015	0.001	0.007	0.015
29	0.022	0.000	0.001	0.014	0.017	0.035	0.015	0.001	0.006	0.013
30	0.015	0.000	0.000	0.008	0.009	0.019	0.008	0.000	0.002	0.007
31	0.012	0.000	0.000	0.007	0.007	0.015	0.006	0.000	0.001	0.005
32	0.009	0.000	0.000	0.005	0.005	0.012	0.004	0.000	0.001	0.005
33	0.015	0.000	0.000	0.008	0.009	0.020	0.009	0.000	0.003	0.008
34	0.022	0.000	0.001	0.014	0.019	0.039	0.014	0.001	0.007	0.015
35	0.028	0.000	0.001	0.016	0.023	0.037	0.016	0.000	0.001	0.019
36	0.000	0.015	0.009	0.000	0.000	0.000	0.000	0.001	0.000	0.000
37	0.000	0.016	0.009	0.000	0.000	0.000	0.000	0.001	0.000	0.000
38	0.000	0.019	0.012	0.000	0.000	0.000	0.000	0.001	0.000	0.000
39	0.017	0.001	0.005	0.012	0.026	0.050	0.012	0.002	0.007	0.015
40	0.021	0.000	0.001	0.013	0.016	0.033	0.014	0.000	0.005	0.012
41	0.022	0.000	0.001	0.014	0.019	0.039	0.014	0.001	0.007	0.015
42	0.018	0.000	0.001	0.011	0.013	0.026	0.012	0.000	0.004	0.010
43	0.017	0.000	0.001	0.011	0.019	0.037	0.012	0.001	0.005	0.012
44	0.017	0.000	0.002	0.011	0.020	0.040	0.012	0.001	0.005	0.013
45	0.021	0.000	0.001	0.013	0.016	0.034	0.014	0.001	0.006	0.014
46	0.021	0.000	0.001	0.013	0.016	0.034	0.014	0.001	0.006	0.014
47	0.018	0.000	0.001	0.011	0.013	0.027	0.012	0.000	0.003	0.011
48	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.028	0.035	0.000	0.001	0.001	0.000	0.009	0.000	0.000
50	0.000	0.032	0.060	0.000	0.002	0.003	0.000	0.016	0.000	0.004

Note: Each cell entry in row i, column j represents the median elasticity of the market share of brand i with respect to the price of brand j, over all 5,988 markets.

Table B.3: Median Own- and Cross-Price Elasticities - Brands 21-30

Brand	21	22	23	24	25	26	27	28	29	30
1	-0.000	-0.001	-0.000	-0.001	0.000	0.000	-0.000	0.000	0.000	-0.002
2	0.000	0.049	0.062	0.084	0.216	0.205	0.027	0.113	0.064	0.062
3	0.000	0.061	0.075	0.102	0.272	0.259	0.033	0.152	0.079	0.073
4	0.000	0.052	0.064	0.088	0.222	0.214	0.028	0.122	0.065	0.064
5	0.000	0.042	0.053	0.073	0.183	0.175	0.024	0.095	0.055	0.054
6	0.000	0.059	0.073	0.100	0.263	0.251	0.033	0.145	0.076	0.071
7	0.000	0.048	0.058	0.081	0.204	0.191	0.025	0.106	0.060	0.060
8	0.000	0.052	0.063	0.089	0.225	0.214	0.028	0.120	0.065	0.063
9	0.000	0.014	0.021	0.025	0.072	0.070	0.009	0.035	0.022	0.016
10	0.000	0.060	0.075	0.101	0.267	0.258	0.033	0.147	0.079	0.073
11	0.000	0.033	0.040	0.055	0.137	0.127	0.017	0.066	0.040	0.042
12	0.002	0.001	0.001	0.002	0.004	0.004	0.001	0.002	0.001	0.001
13	0.000	0.002	0.003	0.004	0.012	0.011	0.002	0.006	0.003	0.003
14	0.000	0.036	0.044	0.060	0.151	0.145	0.020	0.077	0.045	0.046
15	0.000	0.033	0.044	0.056	0.154	0.152	0.018	0.083	0.045	0.039
16	0.000	0.035	0.047	0.059	0.162	0.161	0.019	0.088	0.049	0.042
17	0.000	0.023	0.031	0.040	0.101	0.097	0.014	0.050	0.031	0.028
18	0.000	0.005	0.009	0.008	0.036	0.034	0.003	0.020	0.010	0.005
19	-0.000	0.027	0.040	0.044	0.147	0.146	0.012	0.081	0.043	0.030
20	-0.001	0.040	0.054	0.064	0.191	0.192	0.017	0.100	0.053	0.054
21	2.063	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
22	0.000	-3.315	0.060	0.087	0.212	0.195	0.026	0.109	0.060	0.061
23	0.000	0.065	-4.085	0.111	0.306	0.285	0.035	0.167	0.087	0.080
24	0.000	0.053	0.062	-3.326	0.218	0.199	0.027	0.113	0.061	0.063
25	0.000	0.072	0.095	0.123	-4.011	0.342	0.041	0.210	0.101	0.087
26	0.000	0.076	0.104	0.130	0.394	-4.132	0.045	0.241	0.114	0.090
27	0.000	0.062	0.077	0.105	0.278	0.271	-4.023	0.158	0.081	0.075
28	0.000	0.081	0.117	0.139	0.464	0.461	0.050	-4.210	0.133	0.094
29	0.000	0.074	0.099	0.125	0.371	0.362	0.043	0.221	-4.402	0.089
30	0.000	0.045	0.054	0.076	0.187	0.171	0.023	0.094	0.053	-3.040
31	0.000	0.036	0.045	0.062	0.150	0.142	0.020	0.076	0.044	0.045
32	0.000	0.030	0.037	0.051	0.130	0.121	0.017	0.064	0.038	0.037
33	0.000	0.044	0.053	0.074	0.186	0.174	0.024	0.095	0.054	0.055
34	0.000	0.081	0.123	0.138	0.488	0.490	0.052	0.319	0.140	0.093
35	0.000	0.089	0.129	0.148	0.485	0.498	0.056	0.314	0.149	0.104
36	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.000	0.000
37	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.000	0.000
38	0.000	0.000	0.000	0.001	0.002	0.002	0.000	0.001	0.001	0.000
39	0.000	0.068	0.102	0.116	0.407	0.416	0.038	0.262	0.117	0.079
40	0.000	0.068	0.090	0.116	0.329	0.318	0.039	0.189	0.094	0.083
41	0.000	0.082	0.123	0.139	0.486	0.492	0.052	0.322	0.141	0.094
42	0.000	0.056	0.071	0.096	0.249	0.236	0.030	0.134	0.073	0.070
43	0.000	0.057	0.074	0.096	0.266	0.267	0.031	0.154	0.080	0.070
44	0.000	0.059	0.080	0.100	0.293	0.291	0.032	0.171	0.086	0.072
45	0.000	0.071	0.092	0.118	0.337	0.335	0.040	0.200	0.098	0.084
46	0.000	0.070	0.093	0.118	0.344	0.342	0.040	0.203	0.101	0.085
47	0.000	0.056	0.071	0.096	0.252	0.239	0.031	0.138	0.074	0.069
48	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.001	0.001	0.001	0.002	0.002	0.000	0.001	0.001	0.001
50	0.001	0.001	0.001	0.001	0.004	0.003	0.001	0.002	0.001	0.001

Note: Each cell entry in row i, column j represents the median elasticity of the market share of brand i with respect to the price of brand j, over all 5,988 markets.

Table B.4: Median Own- and Cross-Price Elasticities - Brands 31-40

Brand	31	32	33	34	35	36	37	38	39	40
1	-0.004	-0.007	-0.001	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000
2	0.037	0.041	0.023	0.017	0.002	0.000	0.000	0.000	0.026	0.214
3	0.042	0.049	0.027	0.026	0.002	0.000	0.000	0.000	0.036	0.261
4	0.037	0.042	0.024	0.020	0.002	0.000	0.000	0.000	0.027	0.217
5	0.032	0.036	0.020	0.014	0.001	0.000	0.000	0.000	0.020	0.179
6	0.041	0.047	0.026	0.025	0.002	0.000	0.000	0.000	0.033	0.252
7	0.034	0.039	0.022	0.015	0.001	0.000	0.000	0.000	0.023	0.195
8	0.036	0.041	0.023	0.020	0.002	0.000	0.000	0.000	0.027	0.219
9	0.007	0.003	0.006	0.004	0.000	0.000	0.000	0.000	0.007	0.074
10	0.042	0.048	0.027	0.025	0.002	0.000	0.000	0.000	0.034	0.258
11	0.022	0.024	0.015	0.009	0.001	0.000	0.000	0.000	0.013	0.133
12	0.001	0.001	0.000	0.000	0.000	0.006	0.005	0.003	0.002	0.004
13	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.010	0.011
14	0.026	0.027	0.017	0.011	0.001	0.000	0.000	0.000	0.017	0.152
15	0.022	0.024	0.015	0.009	0.001	0.000	0.000	0.000	0.029	0.155
16	0.024	0.026	0.016	0.010	0.001	0.000	0.000	0.000	0.030	0.165
17	0.015	0.013	0.011	0.007	0.001	0.000	0.000	0.000	0.010	0.102
18	0.002	0.002	0.002	0.002	0.000	0.000	0.000	0.000	0.016	0.032
19	0.012	0.017	0.013	0.006	0.000	0.000	0.000	0.000	0.022	0.150
20	0.029	0.040	0.020	0.011	0.001	0.000	0.000	0.000	0.029	0.193
21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
22	0.033	0.037	0.021	0.018	0.002	0.000	0.000	0.000	0.025	0.201
23	0.044	0.052	0.029	0.030	0.002	0.000	0.000	0.000	0.040	0.289
24	0.034	0.039	0.022	0.019	0.002	0.000	0.000	0.000	0.025	0.205
25	0.048	0.056	0.031	0.037	0.003	0.000	0.000	0.000	0.051	0.333
26	0.051	0.058	0.033	0.044	0.003	0.000	0.000	0.000	0.057	0.367
27	0.044	0.051	0.028	0.027	0.002	0.000	0.000	0.000	0.035	0.265
28	0.052	0.059	0.034	0.055	0.004	0.000	0.000	0.000	0.072	0.418
29	0.050	0.057	0.032	0.040	0.003	0.000	0.000	0.000	0.052	0.345
30	0.030	0.034	0.020	0.014	0.001	0.000	0.000	0.000	0.021	0.182
31	-2.649	0.030	0.017	0.011	0.001	0.000	0.000	0.000	0.016	0.152
32	0.022	-2.272	0.015	0.008	0.001	0.000	0.000	0.000	0.014	0.129
33	0.033	0.038	-3.140	0.014	0.001	0.000	0.000	0.000	0.022	0.181
34	0.051	0.057	0.034	-4.251	0.005	0.000	0.000	0.000	0.078	0.444
35	0.051	0.051	0.032	0.085	-4.251	0.000	0.000	0.000	0.078	0.450
36	0.000	0.000	0.000	0.000	0.000	-1.434	0.001	0.001	0.000	0.001
37	0.000	0.000	0.000	0.000	0.000	0.002	-1.521	0.001	0.000	0.001
38	0.000	0.000	0.000	0.000	0.000	0.003	0.002	-1.877	0.001	0.002
39	0.044	0.051	0.029	0.038	0.003	0.000	0.000	0.000	-4.247	0.372
40	0.047	0.054	0.030	0.034	0.003	0.000	0.000	0.000	0.045	-4.007
41	0.052	0.057	0.034	0.061	0.005	0.000	0.000	0.000	0.077	0.443
42	0.041	0.048	0.026	0.022	0.002	0.000	0.000	0.000	0.031	0.245
43	0.041	0.048	0.027	0.023	0.002	0.000	0.000	0.000	0.046	0.265
44	0.041	0.050	0.027	0.025	0.002	0.000	0.000	0.000	0.054	0.285
45	0.047	0.055	0.031	0.036	0.003	0.000	0.000	0.000	0.048	0.322
46	0.049	0.056	0.031	0.035	0.003	0.000	0.000	0.000	0.049	0.330
47	0.040	0.047	0.025	0.023	0.002	0.000	0.000	0.000	0.033	0.249
48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
49	0.000	0.000	0.000	0.000	0.000	0.007	0.006	0.003	0.001	0.002
50	0.001	0.000	0.000	0.000	0.000	0.006	0.005	0.003	0.004	0.003

Note: Each cell entry in row i, column j represents the median elasticity of the market share of brand i with respect to the price of brand j, over all 5,988 markets.

Table B.5: Median Own- and Cross-Price Elasticities - Brands 41-50

Brand	41	42	43	44	45	46	47	48	49	50
1	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
2	0.026	0.017	0.010	0.011	0.044	0.063	0.037	0.000	0.000	0.000
3	0.036	0.020	0.012	0.014	0.056	0.081	0.043	0.000	0.000	0.000
4	0.028	0.017	0.010	0.011	0.046	0.066	0.037	0.000	0.000	0.000
5	0.020	0.014	0.008	0.009	0.037	0.052	0.031	0.000	0.000	0.000
6	0.034	0.019	0.011	0.013	0.054	0.077	0.043	0.000	0.000	0.000
7	0.023	0.016	0.009	0.010	0.041	0.058	0.032	0.000	0.000	0.000
8	0.028	0.017	0.010	0.011	0.046	0.065	0.037	0.000	0.000	0.000
9	0.007	0.005	0.002	0.002	0.014	0.020	0.009	0.000	0.000	0.000
10	0.035	0.020	0.012	0.013	0.055	0.079	0.044	0.000	0.000	0.000
11	0.014	0.010	0.006	0.006	0.026	0.037	0.021	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.005	0.027
13	0.001	0.001	0.001	0.001	0.002	0.003	0.002	0.000	0.002	0.026
14	0.017	0.012	0.007	0.007	0.030	0.043	0.026	0.000	0.000	0.000
15	0.018	0.011	0.009	0.011	0.030	0.043	0.020	0.000	0.000	0.000
16	0.019	0.012	0.009	0.011	0.032	0.047	0.021	0.000	0.000	0.000
17	0.010	0.008	0.004	0.004	0.020	0.029	0.016	0.000	0.000	0.000
18	0.004	0.001	0.002	0.003	0.007	0.010	0.002	0.000	0.002	0.028
19	0.021	0.008	0.006	0.010	0.029	0.042	0.006	0.000	0.000	0.015
20	0.030	0.024	0.009	0.021	0.045	0.064	0.002	0.000	0.000	0.018
21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.007
22	0.026	0.015	0.009	0.010	0.043	0.060	0.033	0.000	0.000	0.000
23	0.042	0.021	0.013	0.015	0.062	0.089	0.047	0.000	0.000	0.000
24	0.026	0.016	0.010	0.011	0.044	0.061	0.034	0.000	0.000	0.000
25	0.051	0.024	0.015	0.018	0.074	0.105	0.052	0.000	0.000	0.000
26	0.060	0.025	0.016	0.020	0.082	0.116	0.057	0.000	0.000	0.000
27	0.037	0.020	0.012	0.014	0.057	0.080	0.045	0.000	0.000	0.000
28	0.075	0.027	0.018	0.023	0.095	0.136	0.062	0.000	0.000	0.000
29	0.055	0.024	0.015	0.019	0.078	0.112	0.055	0.000	0.000	0.000
30	0.022	0.014	0.008	0.009	0.039	0.054	0.029	0.000	0.000	0.000
31	0.016	0.012	0.006	0.007	0.031	0.043	0.025	0.000	0.000	0.000
32	0.013	0.010	0.006	0.006	0.026	0.037	0.020	0.000	0.000	0.000
33	0.021	0.014	0.008	0.009	0.038	0.054	0.029	0.000	0.000	0.000
34	0.082	0.028	0.019	0.024	0.100	0.143	0.063	0.000	0.000	0.000
35	0.086	0.027	0.019	0.016	0.107	0.145	0.073	0.000	0.000	0.000
36	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.012
37	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.012
38	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.002	0.015
39	0.064	0.023	0.020	0.026	0.078	0.117	0.049	0.000	0.000	0.001
40	0.046	0.023	0.014	0.017	0.068	0.098	0.051	0.000	0.000	0.000
41	-4.320	0.028	0.019	0.024	0.100	0.143	0.063	0.000	0.000	0.000
42	0.031	-3.812	0.011	0.013	0.051	0.074	0.041	0.000	0.000	0.000
43	0.035	0.020	-4.083	0.018	0.055	0.079	0.041	0.000	0.000	0.000
44	0.040	0.021	0.016	-4.187	0.059	0.086	0.041	0.000	0.000	0.000
45	0.050	0.023	0.014	0.018	-4.281	0.102	0.050	0.000	0.000	0.000
46	0.050	0.024	0.015	0.018	0.073	-4.273	0.051	0.000	0.000	0.000
47	0.032	0.019	0.011	0.013	0.052	0.076	-3.802	0.000	0.000	0.000
48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.582	0.000	0.002
49	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	-2.778	0.023
50	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.005	-3.484

Note: Each cell entry in row i, column j represents the median elasticity of the market share of brand i with respect to the price of brand j, over all 5,988 markets.

B.2 Computational Details

My computation approach for estimating the random-coefficients logit demand model follows Nevo (2000b) very closely; however, I incorporate several modest improvements that significantly speed up model convergence without negatively impacting the quality or robustness of the approximation. I start by porting all of the original MATLAB code to the R programming language (R Core Team 2016). In light of the findings in Dubé et al. (2012), I use an inner-loop tolerance of $\varepsilon_{in} = 10^{-14}$ and outer-loop tolerance of $\varepsilon_{out} = 10^{-8}$, significantly increasing the CPU time for the BLP contraction mapping, since it converges linearly. To speed up convergence of the contraction mapping without sacrificing numerical accuracy, I instead use the squared extrapolation method (SQUAREM) algorithm for accelerating fixed-point iterations, which produces faster and more robust convergence than the traditional BLP contraction mapping (Reynaerts et al. 2012; Varadhan 2010). To ensure that the model converges to a global minimum, I estimated the model using ten different sets of starting values for the θ_2 parameters, each set randomly drawn from the standard normal distribution.

Additionally, because the market-level calculations are independent of one another (each t represents a separate DMA-Month), an opportunity exists to drastically improve computational performance by parallelizing computation of the mean utility (δ_{jt}) as well as the Jacobian of the implicit function that defines the mean utility. Computing these values in parallel also requires parallelization of the functions that compute the individual probabilities of choosing each brand (s_{ijt}), the market shares for each brand (s_{jt}), the heteroskedastic nonlinear component of utility (μ_{ijt}), and the BLP contraction mapping. In my case, I set up a socket cluster with 64 nodes on a Windows 7 Server, and the work is distributed to each node on a market-by-market basis using the *doParallel* package in R (Revolution Analytics and Weston 2015). Section B.2.1 provides R code for initialization of the parallel cluster, Section B.2.2 provides modified functions to accommodate parallelization of the mean utility calculation, and Section B.2.3 provides modified functions for parallelization of the Jacobian.

B.2.1 Parallel Cluster Inititalization

```
setupcluster <- function(nc=32) {
  cl <<- makeCluster(nc)
  registerDoParallel(cl)
  ## Find out the names of the loaded packages
  loaded.package.names <- c(sessionInfo()$basePkgs, names( sessionInfo
     ()$otherPkgs ))

  this.env <- environment()
  while( identical( this.env, globalenv() ) == FALSE ) {
    clusterExport(cl,
                  ls(all.names=TRUE, env=this.env),
                  envir=this.env)
    this.env <- parent.env(environment())
  }
  ## repeat for the global environment
  clusterExport(cl,
                ls(all.names=TRUE, env=globalenv()),
                envir=globalenv())

  parLapply( cl, 1:length(cl), function(xx){
    lapply(loaded.package.names, function(yy) {
      require(yy , character.only=TRUE)})
  })
}
```

B.2.2 Parallelized Mean Utility

```
parmeanval <- function(theta2,newvars=c("mvalold"),n.mkt=nmkt) {
```

```
  ## parmeanval serves as a helper function for parallelizing the
     meanval function below, which now includes a index for market
  clusterExport(cl, varlist=newvars)
  f<-foreach(i=1:n.mkt, .combine=c) %dopar% {
    meanval(theta2, id=(cdid==i))
  }
  mvalold<<-f
  return(f)
}

meanval<-function(theta2, id, maxiter=10000, tol=1e-14){
  theta2w<-matrix(0,rtheta,ctheta)
  theta2w[which(theta2w_st!=0)]<-theta2
  expmu<-exp(mufunc(x2,theta2w,id))
  ## Don't start with bad values of delta vector ##
  if (any(is.na(mvalold[id]) | is.infinite(mvalold[id]))) {
    delta_id <- mval_logit[id]
  } else {
    delta_id <- mvalold[id]
  }
  fp<-squarem(par=delta_id, expmu=expmu, s=s_jt[id], fixptfn=blp.inner,
      control=list(tol=tol, maxiter=maxiter))
  return(fp$par)
}

mufunc<-function(x2,theta2w,id){
  #This function computes the non-linear part of the utility
  x2<-x2[id,]
  n<-nrow(x2)
  k<-ncol(x2)
  j<-ncol(theta2w)-1
  mu<-matrix(0,n,ns)
  for (i in 1:ns){
    v_i<-vfull[id,seq(i,k*ns,ns)]
    d_i<-dfull[id,seq(i,j*ns,ns)] # 2256 by 4 take (1,21,41,61)
        (2,22,42,62).. (income,income^2,age,child)
    mu[,i]<-((x2*v_i) %*% (theta2w[,1]))+(x2*(d_i %*% t(theta2w[,(2:(j
        +1))]))) %*% rep(1,k) #theta2w[,1]=sigma and theta2w[,(2:(j+1))
        ]=pi
  }
  return(mu)
}

blp.inner<-function(delta, expmu, s) {
  delta <- delta + log(s) - log(sharefcn(delta,expmu)[[2]])
  return(delta)
}

sharefcn<-function(mval,expmu){
  # This function computes the "individual" probabilities of choosing
     each brand
  # AND the market shares for each product. The output is a list with
      both values
  eg<-expmu*kronecker(t(rep(1,ns)),exp(mval))
```

```
  sum1<-rbind(colSums(eg))
  denom<-1/(1+sum1)
  denom<-denom[rep(1,nrow(eg)),]
  ind.choice<-eg*denom
  choice<-rowSums(ind.choice)/ns
  return(list(ind.choice, choice))
}
```

B.2.3 Parallelized Jacobian

```
parjacob <- function(mval, theta2, n.mkt=nmkt) {
  ## parjacob serves as a helper function for parallelizing the jacobian function below, which now includes a index for market
  f<-foreach(i=1:n.mkt, .combine=rbind) %dopar% {
    jacob(mval, theta2, id=(cdid==i))
  }
  return(f)
}

jacob<-function(mval,theta2,id){
  # This function computes the Jacobian of the implicit function that defines the mean utility
  theta2w<-matrix(0,rtheta,ctheta)
  theta2w[which(theta2w_st!=0)]<-theta2
  expmu<-exp(mufunc(x2,theta2w,id))
  shares<-sharefcn(mval[id],expmu)[[1]] # n x ns
  x2<-x2[id,]
  n<-nrow(x2)
  K<-ncol(x2)
  J<-ncol(theta2w)-1

  theti<-which(theta2w!=0, arr.ind=TRUE)[,1]
  thetj<-which(theta2w!=0, arr.ind=TRUE)[,2]
  rel<-theti+(thetj-1)*max(theti)

  f1<-matrix(0,n,K*(J+1))
  f<-matrix(0,n,length(theti))

  # Computing (partial share)/(partial sigma)
  for (i in 1:K){
    xv<-(x2[,i] %*% t(rep(1,ns)))*vfull[id,((ns*(i-1)+1):(ns*i))]  # n x ns
    sum1<-rbind(colSums(xv*shares))    # 1 x ns
    f1[,i]<-rowMeans(shares*(xv-sum1[rep(1,n),])) # n x 1
  }
  # Computing (partial share)/(partial pi)
  for (j in 1:J){
    d<-dfull[id,((ns*(j-1)+1):(ns*j))]
    temp1<-matrix(0,n,K)
    for (i in 1:K){
      xd<-(x2[,i] %*% t(rep(1,ns)))*d  # n x ns
```

```
      sum1<-rbind(colSums(xd*shares)) # 1 x ns
      temp1[,i]<-rowMeans(shares*(xd-sum1[rep(1,n),])) #n x 1
    }
    f1[,((K*j+1):(K*(j+1)))]<-temp1
  }
  # Computing (partial delta)/(partial theta2)
  temp <- shares
  H1<-temp %*% t(temp)
  H<-(diag(rowSums(temp))-H1)/ns
  f <- -solve(H, tol=1e-20) %*% f1[ ,rel]
  return(f)
}
```

Appendix C: Appendix to Chapter 3

C.1 Additional Tables

(Continued on next page...)

Table C.1: Grower Conferences and Online Grower Listservs Surveyed

Conference / Organization	Dates
Pacific Northwest Vegetable Conference & Trade Show, Kennewick, WA	November 12-13, 2014
29th Annual Southeast Vegetable & Fruit Expo, Myrtle Beach, SC	December 2-3, 2014
Great Lakes Fruit and Vegetable Expo, Grand Rapids, MI	December 9-11, 2014
Southeast Regional Fruit & Vegetable Conference, Savannah, GA	January 8-11, 2015
Future Harvest Chesapeake Alliance for Sustainable Agriculture Conference, College Park, MD	January 15-17, 2015
Ohio Produce Growers & Marketers Association Congress, Sandusky, OH	January 19-21, 2015
Mid-Atlantic Fruit and Vegetable Convention, Hershey, PA	January 27-29, 2015
New Jersey Agricultural Convention and Trade Show, Atlantic City, NJ	February 2-5, 2015
Georgia Fruit & Vegetable Growers Association	January 9, 2014
Michigan State University Extension	December 11, 2014
Future Harvest Chesapeake Alliance for Sustainable Agriculture	January 16, 2015
Center for Produce Safety	February 10, 2015
North Carolina Farm Bureau	January 23, 2015
Ohio State University Extension	January 18, 2015
Oregon State University Extension	January 30, 2015
Pennsylvania Association for Sustainable Agriculture	January 27, 2015
Pennsylvania Vegetable Growers Association	January 26, 2015
University of Florida Extension	January 22, 2015
Virginia Association for Biological Farming	February 8, 2015
Vegetable Growers Association of New Jersey	February 2, 2015
Carolina Farm Stewardship Association	December 8, 2014
Cornell Produce Safety Alliance	December 9, 2014
Michigan Food & Farming Systems	December 9, 2014

Note: The survey closed on May 2, 2015, for all online grower Listservs

Table C.2: Estimated Coefficients for Double Hurdle Specification With No Interactions

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Washing Product	Employee Sanitation & Hygiene	Written Records	Soil Amendment Treatment	Third-Party Audits
Use Variables								
Intercept	-0.4001	-0.6526**	1.4989***	-0.5749*	2.0709***	0.2122	0.7985	-1.8187***
	(0.2756)	(0.2851)	(0.4299)	(0.3057)	(0.214)	(0.3289)	(0.6579)	(0.4246)
Log Fruit and Vegetable Acreage	0.2276***	0.1552***	-0.0872	-0.0391	0.0679	0.1127*	-0.0691	0.3062***
	(0.0477)	(0.0466)	(0.0648)	(0.0487)	(0.0617)	(0.0605)	(0.0684)	(0.0661)
Contractual Obligation	0.4133**	0.6936***	0.5795*	-0.1107	0.1216	1.4203***	0.3883	1.4397***
	(0.2084)	(0.2153)	(0.326)	(0.2335)	(0.3106)	(0.4935)	(0.3829)	(0.2464)
Wholesale / Other Sale Share	0.0013	-0.0015	-0.0026	0.004	-0.0065**	0.0002	-0.0061	0.0006
	(0.0022)	(0.0023)	(0.0033)	(0.0028)	(0.0032)	(0.0031)	(0.0042)	(0.0034)
Sustainable	0.0797	-0.181	0.078	0.8183***	0.1819	0.1331	0.0626	-0.3221
	(0.1835)	(0.1824)	(0.2933)	(0.2413)	(0.2511)	(0.2099)	(0.2386)	(0.3378)
Berries	-0.0067	-0.1248	0.7460***	0.1332	0.4751**	-0.0721	-0.1027	-0.2294
	(0.1576)	(0.1598)	(0.2655)	(0.1824)	(0.1975)	(0.1837)	(0.2313)	(0.2402)
Fruit and Tree Nut	0.116	-0.0539	-0.1435	0.2501	-0.3784*	0.2361	0.0677	-0.0899
	(0.1628)	(0.1658)	(0.273)	(0.1971)	(0.1941)	(0.2017)	(0.2329)	(0.2609)
Vegetables	-0.3321	0.4017*	-0.164	1.2003***	-0.9954***	0.2201	-0.1544	-0.3746
	(0.2312)	(0.233)	(0.3523)	(0.2441)	(0.191)	(0.2766)	(0.6034)	(0.3096)
Expenditure Variables								
Intercept	2.6668***	3.0660***	4.3212***	4.8510***	5.0245***	0.7847***	4.2457***	5.9150***
	(0.4903)	(0.5985)	(0.3617)	(0.8305)	(0.3325)	(0.2859)	(1.2161)	(0.675)
Log Fruit and Vegetable Acreage	0.6955***	0.5608***	0.5475***	0.6816***	0.6319***	0.2560***	0.9180***	0.3798***

Continued. . .

Table C.2 – continued from previous page

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Washing Product	Employee Sanitation & Hygiene	Written Records	Soil Amendment Treatment	Third-Party Audits
	(0.0764)	(0.0795)	(0.0602)	(0.0719)	(0.0542)	(0.0416)	(0.1587)	(0.0986)
Sustainable	0.4638	0.4685	0.6253**	0.7333**	0.2675	0.4459**	0.2322	0.1249
	(0.3922)	(0.3754)	(0.2448)	(0.3231)	(0.2482)	(0.1954)	(0.3848)	(0.5112)
Berries	0.0034	-0.2336	0.1864	-0.1714	-0.125	0.005	-0.0479	1.0149***
	(0.3021)	(0.3223)	(0.226)	(0.2709)	(0.2114)	(0.1675)	(0.4127)	(0.3179)
Fruit and Tree Nut	-0.3933	0.2712	-0.1011	0.3285	-0.0446	-0.3887**	0.241	-0.0873
	(0.3205)	(0.3233)	(0.226)	(0.2798)	(0.2199)	(0.1773)	(0.4118)	(0.3829)
Vegetables	-0.5517	0.2044	0.2788	0.6249	0.0139	-0.3462	0.5856	0.1353
	(0.3793)	(0.4108)	(0.3021)	(0.6044)	(0.2774)	(0.2244)	(1.1349)	(0.3976)
Sigma	1.8964***	1.6828***	1.4946***	1.5790***	1.5092***	1.2357***	1.3839***	1.0722***
	(0.1611)	(0.2371)	(0.0961)	(0.1014)	(0.0716)	(0.0769)	(0.1635)	(0.1031)
Rho	0.9090***	0.8283***	0.6672***	0.2111	0.0001	0.8256***	0.325	-0.2603
	(0.0423)	(0.1378)	(0.2286)	(0.4141)	)	(0.0881)	(0.4009)	(0.2813)
No. of Observations	303	294	297	294	290	286	157	283
Log Likelihood	-389.6464	-347.5561	-428.3126	-442.7636	-496.4305	-453.1219	-198.3643	-164.5507

Note: Standard errors (reported in parentheses) were estimated using the delta method. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10, 5 and 1 percent level, respectively.

Table C.3: Estimated Coefficients for Double Hurdle Specification With Interactions

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Employee Sanitation & Hygiene	Soil Amendment Treatment
Use Variables					
Intercept	-0.3409	-0.6411**	1.4962***	2.0511***	0.7974
	(0.28)	(0.2836)	(0.4332)	(0.4536)	(0.6542)
Log Fruit and Vegetable Acreage	0.2011***	0.1473***	-0.0886	0.0685	-0.069
	(0.0493)	(0.0443)	(0.0652)	(0.0614)	(0.0684)
Contractual Obligation	0.4782**	0.7127***	0.5780*	0.1761	0.3877
	(0.2373)	(0.2022)	(0.3273)	(0.3141)	(0.3852)
Wholesale / Other Sale Share	0.0021	-0.0018	-0.0025	-0.0071**	-0.0061
	(0.0024)	(0.0022)	(0.0033)	(0.0035)	(0.0042)
Sustainable	0.0943	-0.1921	0.0525	0.1678	0.0629
	(0.1863)	(0.1818)	(0.2916)	(0.2562)	(0.2387)
Berries	-0.0724	-0.1226	0.7366***	0.4541*	-0.1022
	(0.1607)	(0.1579)	(0.2641)	(0.2317)	(0.2315)
Fruit and Tree Nut	0.1431	-0.0279	-0.1342	-0.3612	0.0678
	(0.1683)	(0.1655)	(0.274)	(0.2387)	(0.2328)
Vegetables	-0.34	0.4024*	-0.1519	-0.9626**	-0.154
	(0.2357)	(0.2309)	(0.3542)	(0.3936)	(0.5992)
Expenditure Variables					
Intercept	2.8170***	3.5581***	4.1740***	3.6239***	3.6368**
	(0.6047)	(1.0693)	(0.3958)	(0.5814)	(1.5395)
Sustainable	0.49	0.4125	0.6788***	0.1592	0.2349

Continued...

Table C.3 – continued from previous page

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Employee Sanitation & Hygiene	Soil Amendment Treatment
	(0.3559)	(0.3652)	(0.2477)	(0.2416)	(0.3965)
Berries	-0.0768	-0.2777	0.123	-0.278	-0.0504
	(0.2571)	(0.3149)	(0.2318)	(0.2235)	(0.4114)
Fruit and Tree Nut	-0.1766	0.2693	-0.1104	-0.1386	0.2684
	(0.283)	(0.3231)	(0.2267)	(0.2274)	(0.412)
Vegetables	-0.275	0.4475	0.2136	0.1309	0.5797
	(0.3298)	(0.4135)	(0.3072)	(0.298)	(1.1347)
Log Fruit and Veg. Acreage x Water Samples	0.5510***				
	(0.0754)				
Log Fruit and Veg. Acreage x Soil Amendment Samples	0.2094				
	(0.1475)				
Log Fruit and Veg. Acreage x Product Samples	0.0604				
	(0.1126)				
Water Samples	0.0128				
	(0.506)				
Soil Amendment Samples	-0.0747				
	(0.4907)				
Product Samples	1.4928***				
	(0.5315)				
Log Fruit and Veg. Acreage x Flooding		-0.2032			
		(0.6088)			
Log Fruit and Veg. Acreage x Wildlife Intrusion		0.5097***			

Continued. . .

Table C.3 – continued from previous page

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Employee Sanitation & Hygiene	Soil Amendment Treatment
		(0.1049)			
Log Fruit and Veg. Acreage x Other Causes		0.1554			
		(0.1363)			
Log Fruit and Veg. Acreage x Flooding x Wildlife Intrusion		0.2448			
		(0.6166)			
Flooding Inspections		0.1746			
		(1.7905)			
Animal Intrusion Inspections		-0.8544			
		(1.029)			
Other Inspections		-0.0412			
		(0.5903)			
Flooding x Wildlife Intrusion Inspections		0.0268			
		(1.8359)			
Log Fruit and Veg. Acreage x Wash Containers			-0.0291		
			(0.1022)		
Log Fruit and Veg. Acreage x New Containers			0.5607***		
			(0.09)		
New Harvest Containers			0.4063		
			(0.3128)		
Log Fruit and Veg. Acreage x Employee Training				0.0877	
				(0.1305)	
Log Fruit and Veg. Acreage x Toilet/Handwash Facilities				-0.1345	

Continued...

Table C.3 – continued from previous page

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Employee Sanitation & Hygiene	Soil Amendment Treatment
				(0.1323)	
Log Fruit and Veg. Acreage x Equipment Sanitation				0.0337	
				(0.1081)	
Log Fruit and Veg. Acreage x Building Sanitation				0.6863***	
				(0.2062)	
Log Fruit and Veg. Acreage x Sewage/Trash Disposal				-0.1469	
				(0.1905)	
Log Fruit and Veg. Acreage x Other Preventive Actions				0.117	
				(0.1386)	
Employee Education/Training				0.7699*	
				(0.4175)	
Equipment & Tool Sanitation				0.3901	
				(0.3985)	
Building Sanitation				0.1024	
				(0.3516)	
Toilet & Handwashing Facilities				0.1537	
				(0.5569)	
Proper Disposal of Sewage/Trash				0.7019	
				(0.479)	
Other Employee Actions				-0.2481	
				(0.4841)	
Total Number of Employees				0.0012*	

Continued...

Table C.3 – continued from previous page

Variables	Sampling & Testing	Field Inspections	Harvest Container Sanitation	Employee Sanitation & Hygiene	Soil Amendment Treatment
				(0.0007)	
Log Fruit and Veg. Acreage x Single Soil Amendment					1.5959
					(1.078)
Log Fruit and Veg. Acreage x Multiple Soil Amendments					0.8995***
					(0.1626)
Multiple Soil Amendments					0.6437
					(0.9754)
Sigma	1.4970***	1.6996***	1.4895***	1.4037***	1.3782***
	(0.1733)	(0.2066)	(0.0983)	(0.0905)	(0.1636)
Rho	0.7779***	0.8982***	0.6436***	-0.3263	0.325
	(0.1451)	(0.0801)	(0.2563)	(0.5064)	(0.4048)
No. of Observations	303	294	297	290	157
Log Likelihood	-374.9738	-341.5166	-423.2073	-468.5369	-198.1192

Note: Standard errors (reported in parentheses) were estimated using the delta method. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10, 5 and 1 percent level, respectively.

C.2 Survey Instrument

Please answer the following questions to the best of your abilities with respect to the 2014 growing season (unless otherwise noted). Reasonably accurate estimates are acceptable.

Background Information

This is a research project being conducted by Professor Erik Lichtenberg at the University of Maryland, College Park. The purpose of this research is to identify the current prevalence and burden of different food safety risk-reduction strategies for vegetable and fruit growers nationwide.

Your participation in this research study is voluntary. You may choose not to participate. If you decide to participate in this research survey, you may withdraw at any time. The procedure involves filling an online survey that will take approximately 15 to 20 minutes. At the end of this survey, you will be asked if you are interested in providing contact information in order to participate in a follow-up survey. The decision to provide this information is completely voluntary. Your responses will be kept confidential. All data will be stored in a password protected electronic database. The results of this study will be used for scholarly purposes only.

If you have any questions about the research study, please contact Professor Erik Lichtenberg, Department of Agricultural and Resource Economics, University of Maryland, College Park at (301) 405-1279 or elichten@umd.edu. This research has been reviewed according to the University of Maryland IRB procedures for research involving human subjects. If you have questions about your rights as a research participant or wish to report a research-related injury, please contact:

University of Maryland College Park
Institutional Review Board Office
IRB Protocol 11-0513
1204 Marie Mount
College Park, Maryland, 20742
E-mail: irb@umd.edu
Telephone: (301) 405-0678

By clicking the "NEXT" button below you are indicating that you are at least 18 years of age; you have read this consent form or have had it read to you; and you voluntarily agree to participate in this research study.

Do you own or manage a farm?

- ○ Own
- ○ Manage
- ○ Own and Manage
- ○ Neither

Is ALL the produce you grow intended for canning or a similar type of commercial processing that kills pathogens?

- ○ No
- ○ Yes

What vegetables and/or fruit were produced in 2014?

☐ Artichokes	☐ Eggplant	☐ Potatoes and/or Sweet Potatoes
☐ Asparagus	☐ Fresh Herbs	☐ Radishes and/or Turnips
☐ Beans (any type)	☐ Grains, Oilseeds, and/or Hay	☐ Squash (any type) and/or Pumpkins
☐ Beets	☐ Leafy Greens	☐ Sweet Corn
☐ Berries (any type)	☐ Melons (any type)	☐ Tomatoes
☐ Broccoli and/or Cauliflower	☐ Okra	☐ Tree Fruits
☐ Brussel Sprouts	☐ Onions (any type)	☐ Tree Nuts
☐ Carrots	☐ Peas (any type)	☐ Other Vegetables
☐ Celery and/or Rhubarb	☐ Peppers (any type)	☐ Other Fruit
☐ Cucumbers		

Were livestock or other domesticated animals raised on the farm, as well?

○ Yes

○ No

In what county and state are your farm fields located?

State

County

How many *full-time* and *seasonal* employees were employed?

Full-time employees	
Seasonal employees	

In total, how many acres of land were in production?

Vegetables and Fruit	acres
All Farm Production	acres

What was the *total annual revenue* and *total annual expenditures* for all farm production? *Estimates are acceptable.*

Total Annual Revenue	$
Total Annual Expenditures	$

What *share* of total annual revenue and total annual expenditures were attributable to vegetable and fruit production?

Share of Revenue	%
Share of Expenditures	%

Please identify the percentage share of all vegetables and fruit sold directly to the listed entities. ***The column must sum to 100.***

	All Vegetables and Fruit
Direct Sales	0 %
Grocery Retailers	0 %
Foodservice Operations	0 %
Produce Wholesalers/Repackers	0 %
Mass Merchandisers	0 %
Exporters	0 %
Brokers	0 %
Other	0 %
Total	0 %

Did you have any contractual obligation to adhere to any specific safety standards and testing procedures?

- Yes
- No

Please identify the entities with which you had contractual obligations regarding food safety and any corresponding safety standards (e.g., guidance documents, certification programs, USDA GAP, Harmonized GAP, etc.).

	Vegetables and Fruit	Vegetables and Fruit
	Contractual Safety Obligation?	Safety Standard (e.g., GAPs, Certification, etc.)
Grocery Retailers		
Foodservice Operations		
Produce Wholesalers/Repackers		
Mass Merchandisers		
Exporters		
Brokers		
Shippers		
Other:		

For vegetable and fruit production, did operations include the use of a soil amendment or soil treatment that contained animal manures or animal products (e.g., raw manure, compost, fish emulsions, fish meal, blood meal, etc.)?

- Yes
- No

Was more than one soil amendment and/or soil treatment of animal origin used for vegetable and fruit production?

- ◯ Yes
- ◯ No

Were any biological soil amendments of animal origin treated using scientifically-valid physical, chemical or composting processes before application?

- ◯ Yes: All soil amendments were treated.
- ◯ Yes: Some soil amendments were treated, while some were left untreated.
- ◯ No: All soil amendments were untreated.

Was the biological soil amendment of animal origin treated using a scientifically-valid physical, chemical or composting process before application?

- ◯ Yes
- ◯ No

What was the approximate total annual cost of treating biological soil amendments of animal origin before application?
Estimates are acceptable.

$ [ ]

What was the shortest time interval in days between the application of soil amendments of animal origin and harvesting of crops for any growing area on which they were applied?

Treated Soil Amendments	[ ]	days
Untreated Soil Amendments	[ ]	days

End of Survey

Thank you for participating in our survey!
If you are interested in learning the survey results, please contact Erik Lichtenberg at elichten@umd.edu.

Please click NEXT to end the survey.

Sampling & Testing, Wildlife, & Flooding

Was more than one water source used for growing, harvesting, packing, or holding vegetables and fruit?

- ◯ Yes
- ◯ No

What water source(s) was used for growing, harvesting, packing, or holding vegetables and fruit? Please check all that apply.

- ☐ Pond or Lake
- ☐ River
- ☐ Stream or Spring
- ☐ Shallow Well (less than 30 feet)
- ☐ Deep Well (greater than 30 feet)
- ☐ Municipal / City Water
- ☐ Other

Please indicate whether the following samples were collected for microbial testing (e.g., pathogens, generic *E. coli*, coliforms, etc.).
If no samples were taken, please check the last box.

- ☐ Water Samples
- ☐ Soil Amendment and/or Soil Treatment Samples
- ☐ Crop/Product Samples
- ☐ No samples were taken

How frequently were samples collected?

	Weekly	Montlhy	Once a Season	Never	Other
Water	○	○	○	○	○
Soil Amendments and/or Soil Treatments	○	○	○	○	○
Crop/Product	○	○	○	○	○

How frequently were the following samples collected?

Water Samples	
Soil Amendments and/or Soil Treatment Samples	
Crop/Product Samples	

What were the *total annual expenditures* associated with sampling and testing (including employee wages, materials, etc.)?
Estimates are acceptable.

$

Were animals allowed to graze and/or used as working animals in fields where vegetables and fruit is grown?

- ○ Grazing only
- ○ Working Animals only
- ○ Grazing and Working Animals
- ○ Neither

What was the shortest time interval in days between grazing and harvesting of crops for any growing area that was grazed?

[ ] days

Were any measures taken to prevent the introduction of hazards onto covered produce from working animals (e.g., segregated horse paths, etc.)?

- ○ Yes
- ○ No

Were field inspections for flooding, animal intrusion, and/or other contamination sources conducted prior to harvest?
If no field inspections were conducted, please check the last box.

- ☐ Flooding
- ☐ Animal Intrusion
- ☐ Other Contamination Sources [ ]
- ☐ No field inspections were conducted

What was the total annual cost of conducting field inspections (including employee wages, etc.)?
Estimates are acceptable.

$ [ ]

For each of the following, did test results, flooding, animal intrusion, and/or other contamination sources lead to remedial actions (e.g., sanitation, product disposal, water treatment, etc.)?

	Yes	No
Test Results	○	○
Flooding	○	○
Animal Intrusion	○	○
Other Contamination Sources	○	○

Please identify all remedial actions taken following testing, flooding, and/or animal intrusion.

- ☐ Sanitary Surveys/Sanitation
- ☐ Additional Testing
- ☐ Water Treatments
- ☐ Leave enough time between last irrigation and harvest or between harvest and end of storage for microbes to die off
- ☐ Processing/Treatment of Soil Amendments
- ☐ Use of Substitutes for Contaminated Materials
- ☐ Material Disposal
- ☐ Product Disposal

- [ ] Delayed Future Production on Site
- [ ] Other: ______
- [ ] Other: ______

What was the approximate total annual cost associated with these remedial actions (including the value of any disposed materials/products, value of lost future production on site, etc.)?
Estimates are acceptable.

$ ______

Preventive Actions

Were harvest containers washed and/or sanitized prior to harvest for any vegetable or fruit crops?

- ( ) Yes
- ( ) No

Were new harvest containers used for any vegetable or fruit crops?

- ( ) Yes
- ( ) No

For which vegetables and fruit crops were harvest containers washed and/or sanitized prior to harvest?

- [ ] Artichokes
- [ ] Asparagus
- [ ] Beans (any type)
- [ ] Beets
- [ ] Berries (any type)
- [ ] Broccoli and/or Cauliflower
- [ ] Brussel Sprouts
- [ ] Carrots
- [ ] Celery and/or Rhubarb
- [ ] Cucumbers
- [ ] Eggplant
- [ ] Fresh Herbs
- [ ] Grains, Oilseeds, and/or Hay
- [ ] Leafy Greens
- [ ] Melons (any type)
- [ ] Okra
- [ ] Onions (any type)
- [ ] Peas (any type)
- [ ] Peppers (any type)
- [ ] Potatoes and/or Sweet Potatoes
- [ ] Radishes and/or Turnips
- [ ] Squash (any type) and/or Pumpkins
- [ ] Sweet Corn
- [ ] Tomatoes
- [ ] Tree Fruits
- [ ] Tree Nuts
- [ ] Other Vegetables
- [ ] Other Fruit

For which vegetables and fruit crops were new harvest containers used?

- [ ] Artichokes
- [ ] Asparagus
- [ ] Beans (any type)
- [ ] Beets
- [ ] Berries (any type)
- [ ] Broccoli and/or Cauliflower
- [ ] Eggplant
- [ ] Fresh Herbs
- [ ] Grains, Oilseeds, and/or Hay
- [ ] Leafy Greens
- [ ] Melons (any type)
- [ ] Okra
- [ ] Potatoes and/or Sweet Potatoes
- [ ] Radishes and/or Turnips
- [ ] Squash (any type) and/or Pumpkins
- [ ] Sweet Corn
- [ ] Tomatoes
- [ ] Tree Fruits

- [ ] Brussel Sprouts
- [ ] Carrots
- [ ] Celery and/or Rhubarb
- [ ] Cucumbers
- [ ] Onions (any type)
- [ ] Peas (any type)
- [ ] Peppers (any type)
- [ ] Tree Nuts
- [ ] Other Vegetables
- [ ] Other Fruit

What was the total approximate annual cost of washing and/or sanitizing harvest containers (including the cost of disinfectants, employee wages, etc.)?
Estimates are acceptable.

$ ______

What was the total approximate annual cost for the new harvest containers?
Estimates are acceptable.

$ ______

Were any harvested crops/products washed prior to storage or sale?

- ○ Yes
- ○ No

Which vegetable and fruit crops were washed prior to storage or sale?

- [ ] Artichokes
- [ ] Asparagus
- [ ] Beans (any type)
- [ ] Beets
- [ ] Berries (any type)
- [ ] Broccoli and/or Cauliflower
- [ ] Brussel Sprouts
- [ ] Carrots
- [ ] Celery and/or Rhubarb
- [ ] Cucumbers
- [ ] Eggplant
- [ ] Fresh Herbs
- [ ] Grains, Oilseeds, and/or Hay
- [ ] Leafy Greens
- [ ] Melons (any type)
- [ ] Okra
- [ ] Onions (any type)
- [ ] Peas (any type)
- [ ] Peppers (any type)
- [ ] Potatoes and/or Sweet Potatoes
- [ ] Radishes and/or Turnips
- [ ] Squash (any type) and/or Pumpkins
- [ ] Sweet Corn
- [ ] Tomatoes
- [ ] Tree Fruits
- [ ] Tree Nuts
- [ ] Other Vegetables
- [ ] Other Fruit

What was the approximate total annual cost of washing the crops/products (including employee wages, etc.)?
Estimates are acceptable.

$ ______

With regards to employee hygiene and general sanitation, please identify all preventive actions taken. If no action was taken, please check the last box.

- [ ] Employee Education/Training
- [ ] Clean and Accessible Toilet and Handwashing Facilities
- [ ]

Equipment and Tool Sanitation

- ☐ Building Sanitation
- ☐ Proper Disposal of Sewage and Trash
- ☐ Other:
- ☐ Other:
- ☐ No preventive action was taken.

What was the approximate total annual cost associated with these preventive actions?
Estimates are acceptable.

$

Besides field inspections, employee hygiene precautions, general sanitation, washing, sampling, and/or testing, were any other preventive actions taken to directly reduce the risk of pathogen contamination?

- ◯ Yes
- ◯ No

What other preventive actions were taken to directly reduce the risk of pathogen contamination?

What was the total annual cost of implementing these additional preventive actions (including employee wages, cost of materials and equipment, etc.)?
Estimates are acceptable.

$

Do you have a third-party food safety audit program in place?

- ◯ Yes
- ◯ No

What is the total annual cost of these food safety audits?
Estimates are acceptable.

$

Do you keep written records or documentation for any of the following?
If not, please check the last box.

- ☐ Food Hygiene and Food Safety Policies and Procedures
- ☐ Water Treatment Methods

- ☐ Water Treatment Monitoring Results
- ☐ Water Testing Results
- ☐ Soil Amendment and/or Soil Treatement Application Dates
- ☐ Produce/Crop Harvest Dates
- ☐ Soil Amendment and/or Soil Treatement Testing Results
- ☐ Produce/Crop Testing Results
- ☐ Flooding
- ☐ Animal Intrusion
- ☐ Other Contamination
- ☐ No written records or documentation were kept

On a weekly basis, how much time do you spend on record keeping (in hours)?

________ hours

References

Ackerberg, D. A. (2001). Empirically distinguishing informative and prestige effects of advertising. *The RAND Journal of Economics*, 32(2):316–333.

Ackerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44(3):1007–1040.

Adalja, A. A. (2016). Who pays for voluntary quality certification? evidence from the non-gmo project verified label. Working Paper.

Akerlof, G. (1970). The market for lemons: qualitative uncertainlyand market mechanism. *Quarterly Journal of Economics*, 89.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The Economic Journal*, 100(401):464–477.

Antle, J. M. (1999). Benefits and costs of food safety regulation. *Food Policy*, 24(6):605–623.

Antle, J. M. (2000). No such thing as a free safe lunch: the cost of food safety regulation in the meat industry. *American Journal of Agricultural Economics*, 82(2):310–322.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Berry, S., Levinsohn, J., and Pakes, A. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy*, 112(1):68–105.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 25(2):242–262.

Besanko, D., Dubé, J.-P., and Gupta, S. (2005). Own-Brand and Cross-Brand Retail Pass-Through. *Marketing Science*, 24(1):123–137.

Bonroy, O. and Constantatos, C. (2014). On the economics of labels: How their introduction affects the functioning of markets and the welfare of all participants. *American Journal of Agricultural Economics*, 97(1):239–259.

Bourn, D. and Prescott, J. (2002). A comparison of the nutritional value, sensory qualities, and food safety of organically and conventionally produced foods. *Critical reviews in food science and nutrition*, 42(1):1–34.

Bren, L. (2003). Genetic engineering: The future of foods. http://permanent.access.gpo.gov/lps1609/www.fda.gov/fdac/features/2003/603_food.html. Accessed: 30-October-2016.

Carriquiry, M. and Babcock, B. A. (2007). Reputations, market structure, and the choice of quality assurance systems in the food industry. *American Journal of Agricultural Economics*, 89(1):12–23.

Carter, C. A., Grure, G. P., McLaughlin, P., and Maclachlan, M. (2012). California's proposition 37: effects of mandatory labeling of GM food. *ARE Update*, 15(6):3–8.

Chamberlain, G. (1982). Multivariate regression models for panel data. *Journal of Econometrics*, 18(1):5–46.

Chidmi, B. (2012). Vertical relationships in the ready-to-eat breakfast cereal industry in boston. *Agribusiness*, 28(3):241–259.

Costanigro, M. and Lusk, J. L. (2014). The signaling effect of mandatory labels on genetically engineered food. *Food Policy*, 49, Part 1:259–267.

Dannenberg, A., Scatasta, S., and Sturm, B. (2011). Mandatory versus voluntary labelling of genetically modified food: evidence from an economic experiment. *Agricultural Economics*, 42(3):373–386.

Darby, M. R. and Karni, E. (1973). Free competition and the optimal amount of fraud. *Journal of law and economics*, 16(1):67–88.

Desai, P. (2001). Quality Segmentation in Spatial Markets: When Does Cannibalization Affect Product Line Design? *Marketing Science*, 20(3):265–283.

Dranove, D. and Jin, G. Z. (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature*, 48(4):935–963.

Driven to Discover (2012). Cost of food safety: Leafy greens food safety cost study final report. http://safety.cfans.umn.edu/links/costs. Accessed 2015-05-20.

Dubé, J.-P., Fox, J. T., and Su, C.-L. (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica*, 80(5):2231–2267.

Fares, M. and Rouviere, E. (2010). The implementation mechanisms of voluntary food safety systems. *Food Policy*, 35(5):412–418.

FDA (2015). Guidance for industry: Voluntary labeling indicating whether foods have or have not been developed using bioengineering.

Fulponi, L. (2006). Private voluntary standards in the food system: The perspective of major food retailers in oecd countries. *Food Policy*, 31(1):1–13.

Goldberg, P. K. (1995). Product differentiation and oligopoly in international markets: The case of the U.S. automobile industry. *Econometrica*, 63(4):891–951.

Greene, C., Wechsler, S., Adalja, A., and Hanson, J. (2016). Economic Issues in the Coexistence of Organic, Genetically Engineered (GE), and Non-GE Crops. Technical Report EIB-149, USDA ERS.

Grossman, S. J. (1981). The informational role of warranties and private disclosure about product quality. *Journal of Law and Economics*, 24(3):461–483.

Hall, P. K. (2016). Congress finalizes mandatory gmo labeling law. http://nationalaglawcenter.org/congress-finalizes-mandatory-gmo-labeling-law-2/. Accessed: 2016-09-21.

Hardesty, S. D. and Kusunose, Y. (2009). Growers' compliance costs for the leafy greens marketing agreement and other food safety programs. *UC Small Farm Program Brief*, 20.

Hassanein, N. (2011). Matters of scale and the politics of the food safety modernization act. *Agriculture and human values*, 28(4):577–581.

Hennessy, D. A., Roosen, J., and Miranowski, J. A. (2001). Leadership and the provision of safe food. *American Journal of Agricultural Economics*, 83(4):862–874.

Henson, S. and Caswell, J. (1999). Food safety regulation: an overview of contemporary issues. *Food Policy*, 24(6):589–603.

Henson, S. and Reardon, T. (2005). Private agri-food standards: Implications for food policy and the agri-food system. *Food Policy*, 30(3):241–253.

Holleran, E., Bredahl, M. E., and Zaibet, L. (1999). Private incentives for adopting food safety and quality assurance. *Food Policy*, 24(6):669–683.

Hooker, N. H., Nayga, R. M., and Siebert, J. W. (2002). The impact of haccp on costs and product exit. *Journal of Agricultural and Applied Economics*, 34(01):165–174.

Hotelling, H. (1929). Stability in competition. *The Economic Journal*, 39(153):41–57.

Houde, S. (2016). Consumers' Response to Quality Disclosure and Certification: An Application to Energy Labels. Working Paper.

Hughner, R. S., McDonagh, P., Prothero, A., Shultz, C. J., and Stanton, J. (2007). Who are organic food consumers? a compilation and review of why people purchase organic food. *Journal of consumer behaviour*, 6(2-3):94–110.

Jalonick, M. C. (2015). Usda develops new government label for gmo-free products. http://www.washingtonpost.com/national/health-science/usda-develops-certification-labeling-for-gmo-free-foods/2015/05/14/61822a1c-fa54-11e4-9ef4-1bb7ce3b3fb7_story.html. Accessed: 2014-07-03.

Knittel, C. R. and Metaxoglou, K. (2014). Estimation of random-coefficient demand models: Two empiricists' perspective. *Review of Economics and Statistics*, 96(1):34–59.

Knutson, R. D., Palma, M. A., Paggi, M., Seale, J., Ribera, L. A., and Bessler, D. (2014). Role of trade in satisfying us fresh fruit and vegetable demand. *Journal of International Food & Agribusiness Marketing*, 26(4):326–343.

Leggett, C. G. (2002). Environmental Valuation with Imperfect Information: The Case of the Random Utility Model. *Environmental and Resource Economics*, 23(3):343–355.

Lichtenberg, E. and Page, E. T. (2016). Prevalence and cost of on-farm produce safety measures in the mid-atlantic. *Food Control*, 69:315–323.

Loader, R. and Hobbs, J. E. (1999). Strategic responses to food safety legislation. *Food Policy*, 24(6):685–706.

Low, Sarah A, e. a. (2015). Trends in us local and regional food systems: A report to congress. *USDA Economic Research Service*, AP-068.

Lowe, P. (2016). Senators reach deal on national gmo labeling bill. http://www.npr.org/sections/thesalt/2016/06/23/483290269/senate-unveils-a-national-gmo-labeling-bill. Accessed: 23-June-2016.

Lusk, J. L., Jamal, M., Kurlander, L., Roucan, M., and Taulman, L. (2005). A meta-analysis of genetically modified food valuation studies. *Journal of Agricultural and Resource Economics*, 30(1):28–44.

MacDonald, J. M. and Crutchfield, S. (1996). Modeling the costs of food safety regulation. *American Journal of Agricultural Economics*, 78(5):1285–1290.

Martinez, Steve, e. a. (2010). Local food systems: Concepts, impacts, and issues. *USDA Economic Research Service*, ERR 97.

McCluskey, J. (2000). A game theoretic approach to organic foods: An analysis of asymmetric information and policy. *Agricultural and Resource Economics Review*, 29(1):1–9.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, pages 105–142.

Milgrom, P. and Roberts, J. (1986). Relying on the information of interested parties. *RAND Journal of Economics*, 17(1):18–32.

Moorthy, K. S. (1984). Market segmentation, self-selection, and product line design. *Marketing Science*, 3(4):288–307.

Mussa, M. and Rosen, S. (1978). Monopoly and product quality. *Journal of Economic Theory*, 18(2):301–317.

Muth, M. K., Wohlgenant, M. K., Karns, S. A., and Anderson, D. W. (2003). Explaining plant exit in the us meat and poultry industries. *Journal of Agricultural & Food Industrial Organization*, 1(1):7.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, 78(2):311–329.

Nevo, A. (2000a). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, pages 395–421.

Nevo, A. (2000b). A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics and Management Strategy*, 9(4):513–548.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342.

Nevo, A. and Wolfram, C. (2002). Why do manufacturers issue coupons? an empirical analysis of breakfast cereals. *RAND Journal of Economics*, pages 319–339.

Non-GMO Project (2014a). Faqs-product verification. http://www.nongmoproject.org/product-verification/faqs/. Accessed: 2014-08-09.

Non-GMO Project (2014b). Gmo facts. http://www.nongmoproject.org/learn-more/. Accessed: 2014-08-09.

Non-GMO Project (2014c). *Non-GMO Project Standard*. Non-GMO Project, Bellingham, Washington. Available at: http://www.nongmoproject.org/wp-content/uploads/2014/06/Non-GMO-Project-Standard-v11.pdf.

Non-GMO Project (2014d). The non-gmo project verified seal. http://www.nongmoproject.org/learn-more/understanding-our-seal/. Accessed: 2014-08-09.

Non-GMO Project (2014e). What is GMO? http://www.nongmoproject.org/learn-more/what-is-gmo/. Accessed: 2014-08-09.

Non-GMO Project (2017). History. https://www.nongmoproject.org/about/history/. Accessed: 2017-05-04.

Onyango, B., Nayga, R. M., and Govindasamy, R. (2006). U.s. consumers' willingness to pay for food labeled 'genetically modified'. *Agricultural and Resource Economics Review*, 35(2):299.

Paggi, M. S., Yamazaki, F., Ribera, L., Palma, M., and Knutson, R. (2013). Domestic and trade implications of leafy green marketing agreement type policies and the food safety modernization act for the southern produce industry. *Journal of Agricultural and Applied Economics*, 45(3):453–64.

Painter, John A, e. a. (2013). Attribution of foodborne illnesses, hospitalizations, and deaths to food commodities by using outbreak data, united states, 1998–2008. *Emerging Infectious Disease*, 19(3):407–415.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, 110(4):705–729.

R Core Team (2016). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Revolution Analytics and Weston, S. (2015). *doParallel: Foreach Parallel Adaptor for the 'parallel' Package*. R package version 1.0.10.

Reynaerts, J., Varadhan, R., and Nash, J. C. (2012). The Convergence Properties of the BLP (1995) Contraction Mapping and Alternative Algorithms in R. *VIVES Discussion Paper*, (35).

Ribera, L., Knutson, R., Paggi, M., Yamazaki, F., Palma, M., and Anciso, J. (2014). Impacts of evolving food safety standards on the sustainability of small- and medium-size produce farms: Implications for implementation of the fda food safety modernization act: Final report. Technical Report USDA-NIFA Award No. 2012-68006-30187.

Ribera, L. A. and Knutson, R. D. (2011). The fda's food safety modernization act and its economic implications. *Choices*, 26(4):16–21.

Ribera, L. A., Palma, M. A., Paggi, M., Knutson, R., Masabni, J. G., and Anciso, J. (2012). Economic analysis of food safety compliance costs and foodborne illness outbreaks in the united states. *HortTechnology*, 22(2):150–156.

Ribera, L. A., Yamazaki, F., Paggi, M., Seale Jr, J. L., et al. (2016). The food safety modernization act and production of specialty crops. *Choices*, 31(1).

Richards, T. J. and Hamilton, S. F. (2015). Variety pass-through: An examination of the ready-to-eat breakfast cereal market. *Review of Economics and Statistics*, 97(1):166–180.

Richards, T. J. and Patterson, P. M. (2006). Firm-level competition in price and variety. *Journal of Agricultural and Applied Economics*, 38:491–512.

Roe, B. and Sheldon, I. (2007). Credence good labeling: The efficiency and distributional implications of several policy approaches. *American Journal of Agricultural Economics*, 89(4):1020–1033.

Roe, B. and Teisl, M. F. (2007). Genetically modified food labeling: The impacts of message and messenger on consumer perceptions of labels and products. *Food Policy*, 32(1):49–66.

Rouvière, E. and Caswell, J. A. (2012). From punishment to prevention: A french case study of the introduction of co-regulation in enforcing food safety. *Food Policy*, 37(3):246–254.

Scherer, F. M. (1979). The welfare economics of product variety: an application to the ready-to-eat cereals industry. *The Journal of Industrial Economics*, pages 113–134.

Schmalensee, R. (1978). Entry Deterrence in the Ready-to-Eat Breakfast Cereal Industry. *The Bell Journal of Economics*, 9(2):305–327.

Segerson, K. (1999). Mandatory vs. voluntary approaches to food safety. *Agribusiness*, 15(1):53–70.

Stone, R. (1954). Linear expenditure systems and demand analysis: an application to the pattern of british demand. *The Economic Journal*, pages 511–527.

Thomas, L. A. (1999). Incumbent firms' response to entry: Price, advertising, and new product introduction. *International Journal of Industrial Organization*, 17(4):527–555.

Thompson, E., Harper, A. M., and Kraus, S. (2008). Think globally–eat locally: San francisco foodshed assessment. *American Farmland Trust*, 23.

Unnevehr, L. J. and Jensen, H. H. (1999). The economic implications of using haccp as a food safety regulatory standard. *Food Policy*, 24(6):625–635.

Varadhan, R. (2010). Squarem: Squared extrapolation methods for accelerating fixed-point iterations. http://CRAN.R-project.org/package=SQUAREM, Rpackageversion. Accessed: 2017-04-28.

Viscusi, W. K. (1978). A Note on "Lemons" Markets with Quality Certification. *The Bell Journal of Economics*, 9(1):277–279.

Yiridoe, E. K., Bonti-Ankomah, S., and Martin, R. C. (2005). Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: a review and update of the literature. *Renewable Agriculture and Food Systems*, 20(04):193–205.