Voluntary Quality Disclosure in Credence Good Markets

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Abstract

This paper empirically examines firm response to a voluntary quality certification program for non-GMO food products using U.S. supermarket retail point-of-sale data and product certification data from the Non-GMO Project. First, using a hedonic framework, I find no evidence of price premiums or quantity changes for newly certified non-GMO food products across 18 food categories, but I find support for the hypothesis that the certification may induce other strategic firm response such as new non-GMO product development. I then develop a structural demand model to investigate 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 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. This paper builds on previous studies examining the role of non-price marketing strategies in the RTE cereal industry; it is the first to examine how voluntary quality certification impacts demand for RTE cereal. More broadly, it makes an empirical contribution to the literature on voluntary quality disclosure in credence good markets.

JEL: L15, L66, Q18, D22
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[†]Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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 examines the impact of voluntary quality certification on demand in the ready-to-eat [RTE] cereal industry, using evidence from from a voluntary non-GMO certification in the U.S food industry. 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.

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 that obtain the certification feature an easily recognizable label[1] on their packaging that reads, "Non-GMO Project Verified" (See Figure 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.

[Figure 1 about here.]

The goal of this paper is to determine whether firms use a voluntary, non-GMO quality certification to extract price premiums[2] or increase market share for newly certified food products, and whether these strategies evolve over time. Specifically, I estimate a discrete-choice, random 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

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

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

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 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 1 provides institutional details and discusses the literature on quality disclosure and labeling, willingness-to-pay for non-GMO products, and demand estimation in the RTE cereal industry. Section 2 presents the theoretical framework for the structural economic model and welfare analysis. Section 3 describes the data sources I employ to implement this study. Section 4 provides preliminary evidence using a simple hedonic model to estimate non-GMO price premiums and quantities sold. Section 5 highlights the empirical strategy I use to estimate the demand system. Section 6 presents parameter estimates recovered from the model and the simulated welfare effects of non-GMO labeling. Lastly, Section 7 offers concluding remarks as well as opportunities for future extensions to the analysis.

1 Background

1.1 Institutional Details

In the U.S., over 90% of canola, corn, cotton, soybeans, and sugar beets are GMO.[3] Most GMO seed varieties are modified to carry several input-traits designed to benefit producers, the most common of which are herbicide tolerance[4] and insect resistance.[5] 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.

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 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

[3]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.

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

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

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.[6] and Canada employing a voluntary non-GMO labeling regime, while the European Union, Australia, New Zealand, and Japan use 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,[7] 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,

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

[7] 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.

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, 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 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[8] 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[9] as well as rigorous traceability 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

[8]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).

[9]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).

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 label has grown rapidly since 2010; the Non-GMO Project currently verifies over 3,000 brands that represent more than 43,000 products and $19.2 billion in sales (Non-GMO Project 2017). Figure 2 shows the monthly cumulative growth in products using the label by Organic status. The label launched with about 200 products in 2010 and included 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 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.

[Figure 2 about here.]

[Figure 3 about here.]

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).

1.3 Relevant Literature

1.3.1 Quality Disclosure & Labeling

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,[10] 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.[11] 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 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.

1.3.2 Willingness-to-Pay for Non-GMO

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

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

[11] 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).

(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. Kalaitzandonakes et al. (2018) employs hedonic modeling to estimate retail price premiums for non-GMO and organic products across four food categories, including RTE cereal, between 2009 to 2016 using monthly retail scanner data. They find price premiums between 9.8% to 61.8% for non-GMO products in their sample.

1.3.3 Demand Estimation in the 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.[12] 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

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

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 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 Conceptual Model

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.

2.1 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

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{1}$$

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

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \quad v_i \sim P_v(v), \quad D_i \sim P_D(D), \tag{2}$$

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

$$s_{jt}(x, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP(D, v, \varepsilon) = \int_{A_{jt}} dP_\varepsilon(\varepsilon) dP_v(v) dP_D(D), \tag{3}$$

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

2.2 Firm Behavior

Assume there are $f = 1, \ldots, F$ 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

$$p - mc = \Omega^{-1} s(p). \tag{4}$$

Once demand parameters are recovered, Equation 4 can be used estimate marginal costs for each brand.

3 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.

3.1 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 3.3 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.[13] I then examine the portfolio of

[13]These are brands that entered the market between 2010 and 2014 with Non-GMO Project Verification

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 1 presents summary statistics by brand for the variables used in the estimation.

[Table 1 about here.]

3.2 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 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. Figure 4 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.

[Figure 4 about here.]

3.3 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

already in place *prior to* appearing in the Nielsen data.

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.

3.4 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 contains summary statistics by DMA for the demographic variables used in estimation.

[Table 2 about here.]

4 Preliminary Evidence

To help motivate development of the demand model, this section explores whether firms use the voluntary non-GMO label to extract rent and pass the certification cost to consumers and provides preliminary evidence that firms respond strategically to voluntary non-GMO labeling for food products. First, 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 using weekly, product-level Nielsen retail scanner data for 18 product categories from U.S. supermarkets from 2009 to 2014. I find no evidence of price premiums or changes to quantity sold for newly certified non-GMO food products. I then investigate alternative 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.

4.1 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 3 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. Of course, RTE 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 will provide a benchmark for our demand estimation 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.

[Table 3 about here.]

Figure 5 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.

[Figure 5 about here.]

4.2 Hedonic 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.[14] 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

[14]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.

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.[15]

4.2.1 Price Premiums

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 explore dynamic effects of the label in greater detail,

$$\begin{aligned}\log(p_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ & + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt}\end{aligned} \tag{5}$$

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.

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

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

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.

4.2.2 Quantity Sold

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,

$$\begin{aligned} \log(q_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ & + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \end{aligned} \tag{6}$$

where the treatment indicators are the same as in Equation 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.

4.2.3 Identification

Each of the specifications introduced above includes fixed effects to control for unobserved heterogeneity across product UPC and week-manufacturer-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 4. 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.

[Table 4 about here.]

4.3 Results

4.3.1 Price Premiums

Table 5 presents the price premium regression results based on the model specified in the Equation 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.[16] 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.

In the final specification with the full suite of UPC and Week×Category×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

[16]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.

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 3 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.

Table 6 presents the price premium regression results based on Equation **??** 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 **??**. 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.[17] 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.[18] Therefore, I cannot conclude that organic products command smaller price

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

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

premiums for non-GMO certification than non-organic products.

[Table 5 about here.]

[Table 6 about here.]

4.3.2 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 7 presents results for the quantity regression estimates based on Equation 6. 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.

[Table 7 about here.]

4.4 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.

4.4.1 Timing of Certification

Figure 6 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.

[Figure 6 about here.]

To delve more into Figure 6, Table 8 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.

[Table 8 about here.]

4.4.2 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.[19] 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 9 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 cost to consumers.

[Table 9 about here.]

4.5 Discussion

This preliminary evidence warrants 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 structural model that can account for market structure and

[19] 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.

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.

5 Structural Estimation

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 1 and 2 to express utility as

$$\begin{aligned} u_{ijt} &= \delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) + \varepsilon_{ijt}, \\ \delta_{jt} &= x_{jt}\beta - \alpha p_{jt} + \xi_j + \xi_t + \Delta\xi_{jt}, \quad \mu_{ijt} = [-p_{jt}, x_{jt}]' * (\Pi D_i + \Sigma v_i). \end{aligned} \tag{7}$$

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

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{K} \exp(\delta_{kt} + \mu_{ikt})} \tag{8}$$

and product market shares as

$$s_{jt} = \frac{\sum_{i=1}^{I_t} s_{ijt}}{I_t}. \tag{9}$$

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

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\ \omega(\theta)' Z A^{-1} Z' \omega(\theta) \tag{10}$$

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 9 with observed market shares from the data:

$$s(\delta_{\cdot t}; \theta_2) = S_{\cdot t} \tag{11}$$

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

$$\delta_{\cdot t}^{(k+1)} = \delta_{\cdot t}^{(k)} + \ln S_{\cdot t} - \ln s(\delta_{\cdot t}^{(k)}; \theta_2), \tag{12}$$

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

$$\omega_{jt} = \delta_{jt}(S_{\cdot t}; \theta_2) - x_{jt}\beta - \alpha p_{jt} \tag{13}$$

and used directly in Equation 10. The elements of θ_1 in Equation 13 are obtained using linear instrumental variables regression. Nevo (2000b) and Nevo (2001) provide additional details on the estimation strategy, and Appendix C 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

$$\frac{\partial s_j(p)}{\partial p_k} = \begin{cases} \frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}(1-s_{ijt}) & \text{if } j=k, \\ -\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}s_{ikt} & \text{otherwise.} \end{cases} \tag{14}$$

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

$$\eta_{jkt} = \begin{cases} \frac{p_{jt}}{s_{jt}}\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}(1-s_{ijt}) & \text{if } j=k, \\ -\frac{p_{kt}}{s_{jt}}\frac{1}{I_t}\sum_i^{I_t} \alpha_i s_{ijt}s_{ikt} & \text{otherwise.} \end{cases} \tag{15}$$

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

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 7, 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.

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,[20] 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

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

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 6.2.

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.[21] 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.[22]

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

$$CV_i^P = \frac{1}{\alpha_i}\left[\ln \sum_{j=0}^{J} \exp(\tilde{V}_{ij}) - \ln \sum_{j=0}^{J} \exp(V_{ij})\right], \tag{16}$$

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. Accord-

[21] 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.

[22] 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.

ingly, 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

$$CV_i^I = \frac{1}{\alpha_i}\left[\ln\sum_{j=0}^{J}\exp(\tilde{V}_{ij}) + \sum_{j=0}^{J}\tilde{s}_{ij}(\tilde{V}_{ij}^E - \tilde{V}_{ij})\right] - \frac{1}{\alpha_i}\left[\ln\sum_{j=0}^{J}\exp(V_{ij}) + \sum_{j=0}^{J}s_{ij}(V_{ij}^E - V_{ij})\right], \tag{17}$$

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 17 differs from the perfect information welfare measure in Equation 16 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 17 reduces to the perfect information welfare measure in 16.

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 17 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 16 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.

6 Results

6.1 Logit Specification

In Equation 7, 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 11 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 10 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 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.

[Table 10 about here.]

6.2 Full Model

The results for the full random coefficients logit model are presented in Table 11. 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 our hedonic analysis 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.[23] 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.

[Table 11 about here.]

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 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.[24]

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

[23] 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.

[24] I also calculate own- and cross-price elasticities from the model using Equation 15. 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 16, 17, 18, 19, and 20.

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 7. 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.

[Figure 7 about here.]

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 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 14. Then I construct the ownership matrix Ω^o for the 50 brands used in the estimation to calculate price-cost margins using Equation 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 12.

[Table 12 about here.]

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 7 and new product market shares using Equation 9. With updated market shares, new revenue and profit can be calculated for each brand to assess how each labeling scenario impacts firm profitability. Table 13 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.

[Table 13 about here.]

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 16 and 17 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 14, 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.

[Table 14 about here.]

7 Conclusion

In this paper, I investigate how a voluntary, third-party non-GMO certification impacts demand in the RTE cereal industry in the U.S. First, I use a hedonic framework to estimate price premiums and quantity changes for newly certified non-GMO food products across 18 food categories. I find no statistically significant price premiums or quantity changes for newly certified non-GMO food products, but I find suggestive evidence that the label may induce other firm strategies such as new non-GMO product development targeted to specific consumers. I estimate 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. More broadly, it contributes to our understanding of how voluntary quality disclosure affects demand in credence good markets.

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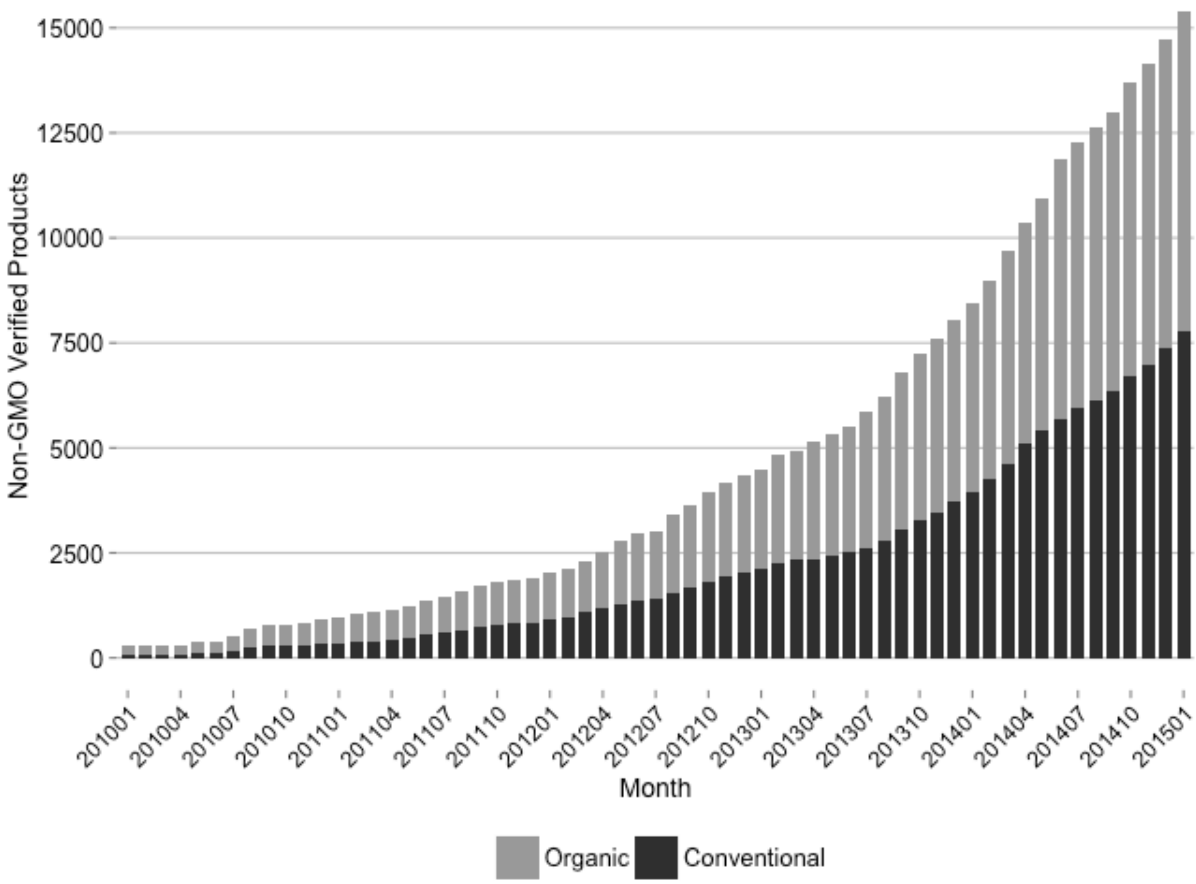
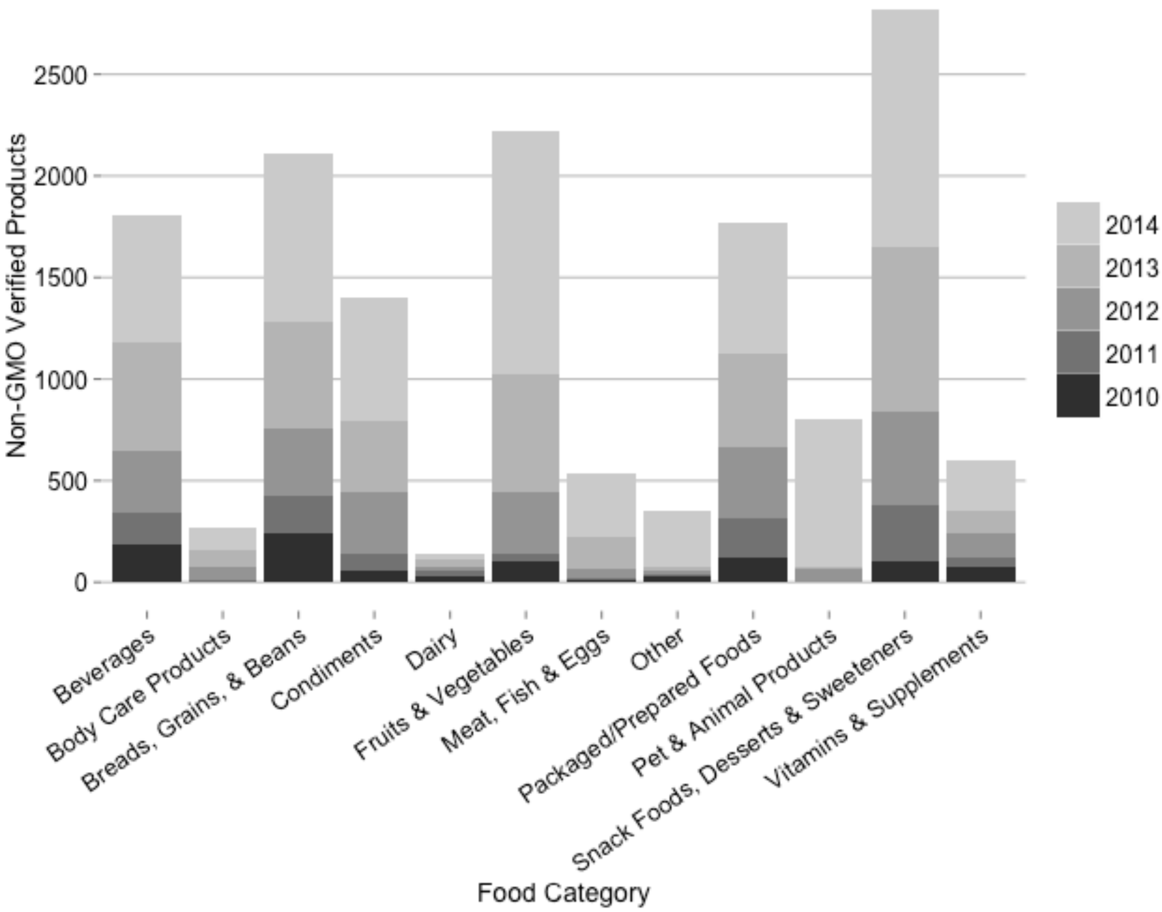
Source: The Non-GMO Project, 2016.

Figure 1: Non-GMO Project Verified Label



Note: Product counts are not unique by package specification.

Figure 2: Cumulative Monthly Non-GMO Project Verified Products by Organic Status



Note: Product counts are not unique by package specification.

Figure 3: Growth in Non-GMO Project Verified Products by Product Category

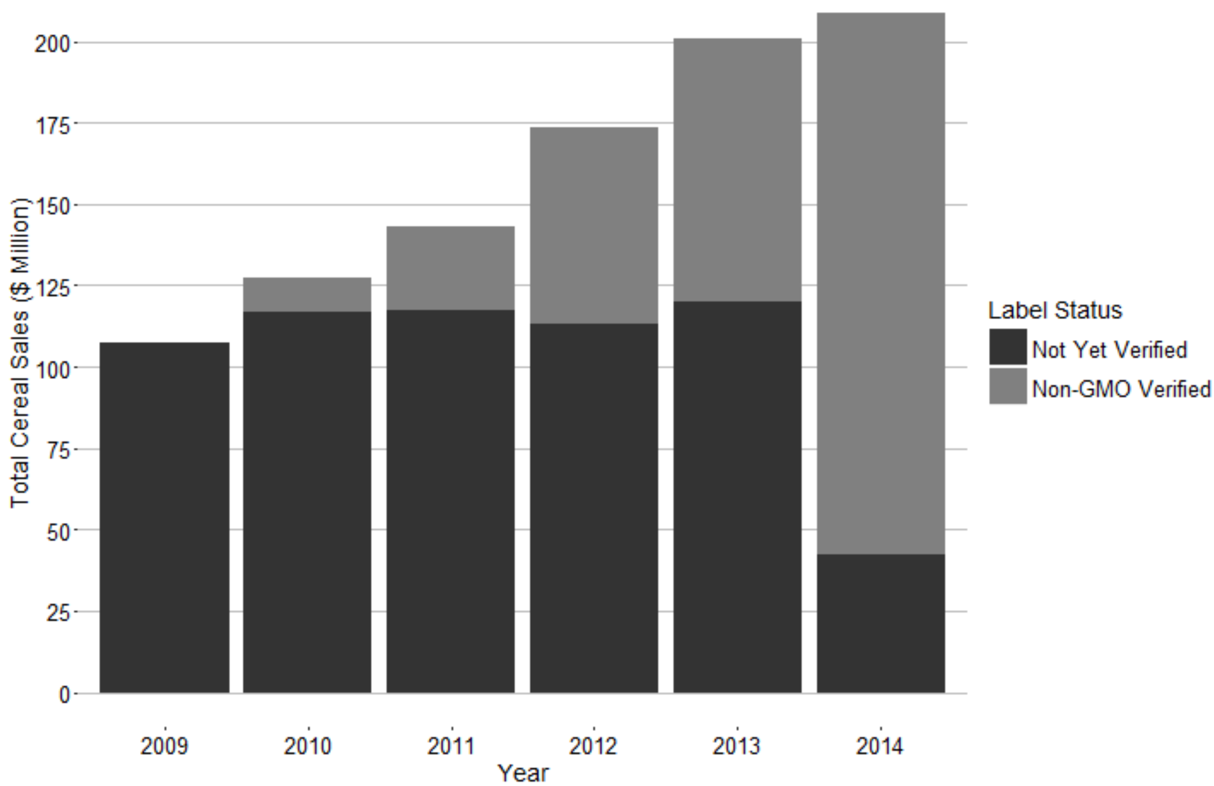


Figure 4: Annual Non-GMO Project Verified RTE Cereal Sales

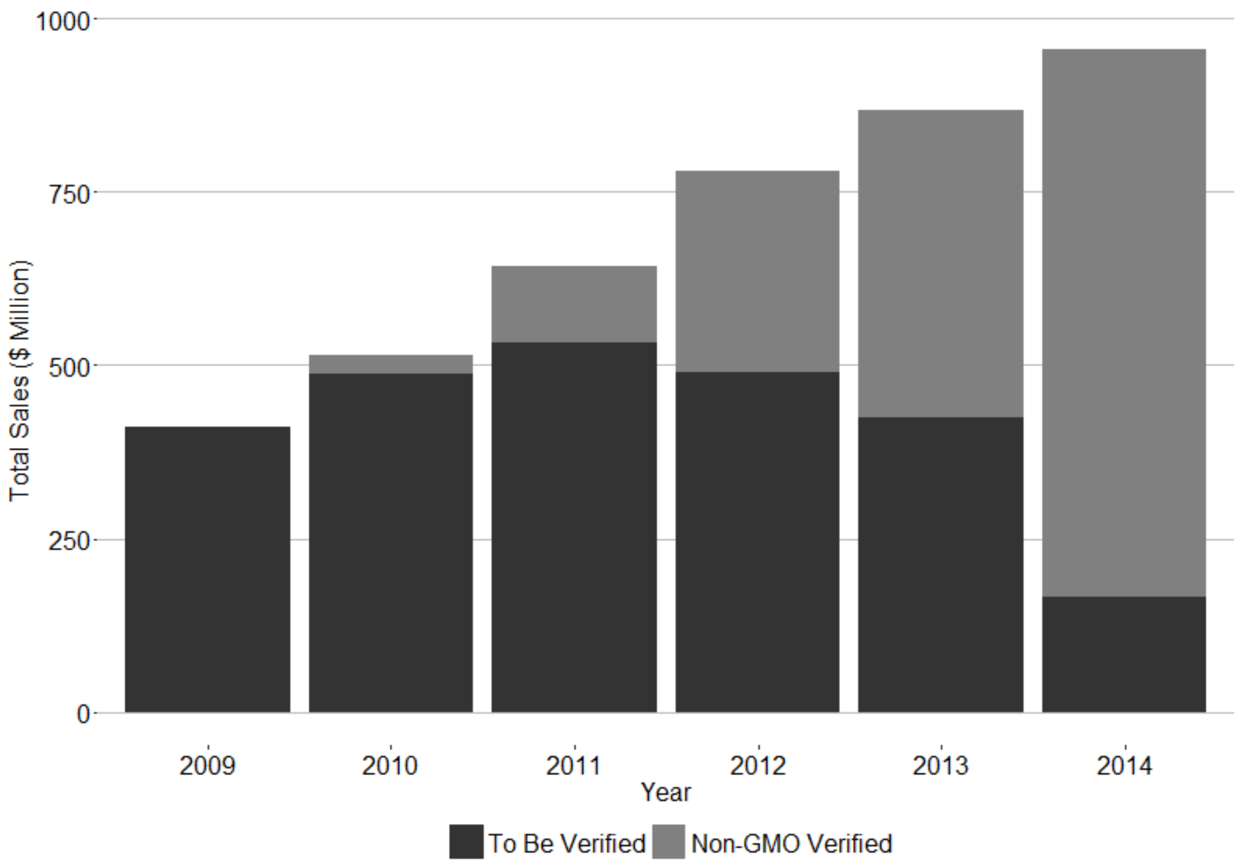
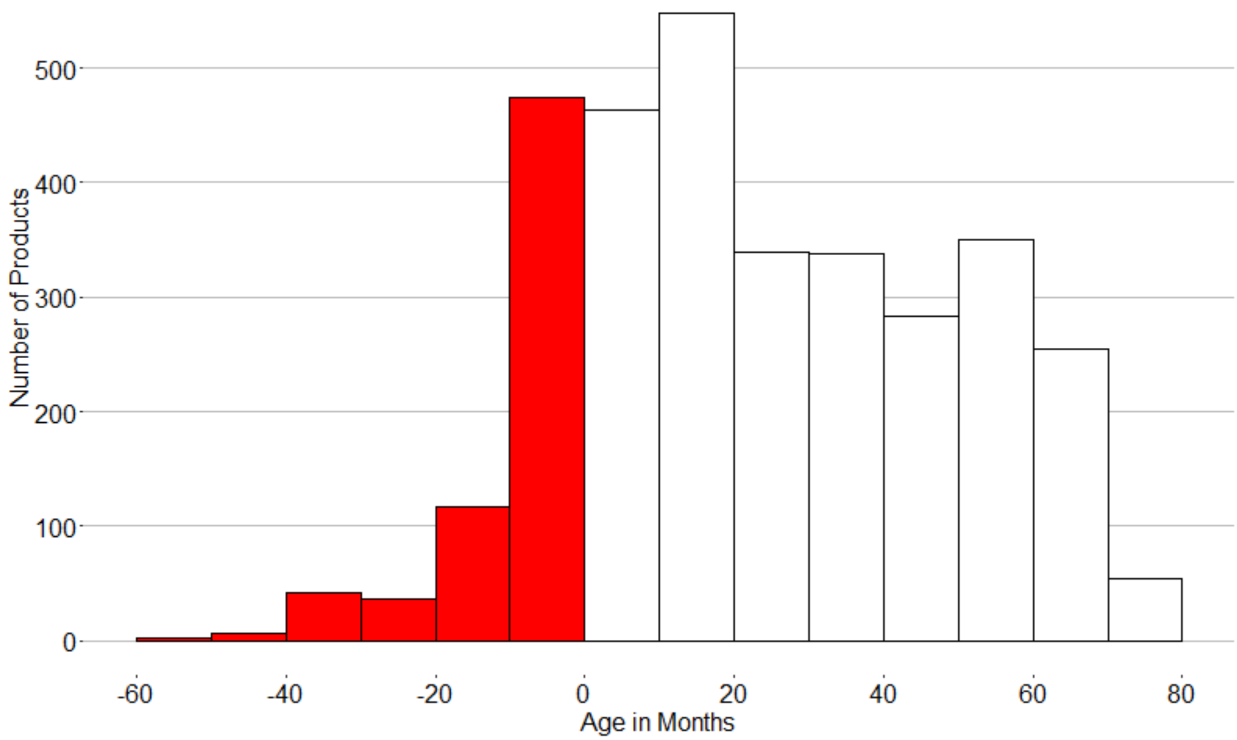


Figure 5: Annual Non-GMO Project Verified Product Sales



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

Figure 6: Product Age When Non-GMO Project Verified

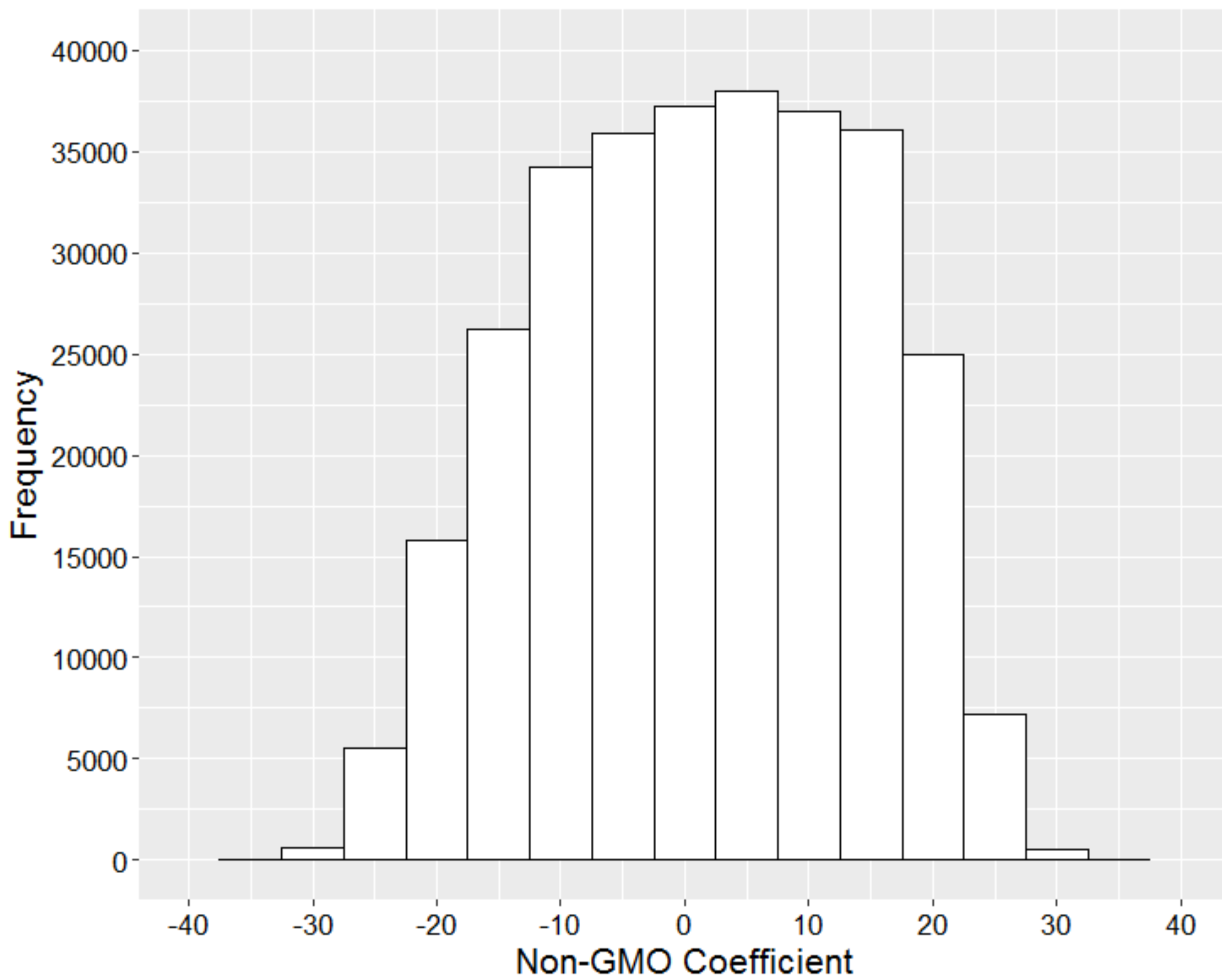


Figure 7: Distribution of Non-GMO Label Coefficient

Table 1: Summary Statistics

Brand	Non-GMO	Price Avg.	Price StDev	Label Avg.	Market Share Avg.	Market Share StDev	No. Markets
01	Yes	0.386	0.064	0.296	0.000	0.000	5306
02	No	0.211	0.019	–	0.013	0.006	5988
03	No	0.195	0.018	–	0.012	0.005	5988
04	No	0.209	0.021	–	0.003	0.002	5988
05	No	0.222	0.026	–	0.001	0.001	5988
06	No	0.198	0.019	–	0.020	0.008	5988
07	No	0.215	0.029	–	0.002	0.001	5988
08	No	0.209	0.021	–	0.010	0.004	5988
09	No	0.267	0.026	–	0.005	0.002	5988
10	No	0.196	0.019	–	0.004	0.002	5988
11	No	0.238	0.031	–	0.003	0.002	5988
12	Yes	0.199	0.022	1.000	0.001	0.000	3131
13	Yes	0.203	0.017	0.749	0.001	0.001	4788
14	Yes	0.232	0.020	0.017	0.001	0.001	5988
15	Yes	0.220	0.020	0.182	0.002	0.001	5988
16	Yes	0.217	0.018	0.182	0.003	0.002	5988
17	No	0.254	0.021	–	0.002	0.001	5988
18	Yes	0.206	0.027	0.595	0.000	0.000	5795
19	Yes	0.199	0.020	0.376	0.001	0.000	3846
20	Yes	0.208	0.022	0.021	0.001	0.001	1226
21	Yes	0.334	0.050	0.588	0.000	0.000	5759
22	No	0.214	0.026	–	0.005	0.002	5988
23	No	0.187	0.019	–	0.005	0.002	5988
24	No	0.213	0.023	–	0.008	0.003	5988
25	No	0.172	0.021	–	0.017	0.008	5988
26	No	0.161	0.014	–	0.016	0.008	5988
27	No	0.193	0.022	–	0.002	0.002	5985
28	No	0.140	0.015	–	0.009	0.004	5988
29	No	0.167	0.016	–	0.005	0.002	5988
30	No	0.222	0.022	–	0.006	0.003	5988
31	No	0.234	0.018	–	0.004	0.002	5988
32	No	0.242	0.020	–	0.005	0.003	5988
33	No	0.222	0.019	–	0.002	0.001	5988
34	No	0.126	0.023	–	0.003	0.003	5972
35	Yes	0.122	0.025	–	0.000	0.000	3444
36	Yes	0.271	0.054	0.900	0.000	0.000	5927
37	Yes	0.268	0.058	0.901	0.000	0.000	5661
38	Yes	0.258	0.050	0.898	0.000	0.000	5829
39	Yes	0.139	0.017	0.165	0.003	0.002	5988

Continued. . .

Table 1 – continued from previous page

Brand	Non-GMO	Price Avg.	Price StDev	Label Avg.	Market Share Avg.	Market Share StDev	No. Markets
40	No	0.180	0.016	–	0.017	0.009	5988
41	No	0.128	0.015	–	0.003	0.002	5988
42	No	0.201	0.021	–	0.001	0.001	5980
43	Yes	0.188	0.022	0.096	0.001	0.001	5768
44	Yes	0.179	0.025	0.116	0.001	0.001	5988
45	No	0.176	0.021	–	0.004	0.003	5988
46	0.174	0.021	–	0.005	0.003	5988	
47	No	0.199	0.030	–	0.003	0.002	5984
48	Yes	0.310	0.050	0.779	0.000	0.000	5266
49	Yes	0.231	0.060	0.982	0.000	0.000	3336
50	Yes	0.207	0.018	1.000	0.000	0.000	2454

Table 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
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

Continued...

Table 2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
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
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

Continued. . .

Table 2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
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
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

Continued. . .

Table 2 – continued from previous page

Designated Marketing Area (DMA)	Outside Market Share	Average Population	Average Income	Average Age	Average Child
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
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 3: 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 4: 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 5: 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 6: 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$^{\cdot}$	−0.022$^{\cdot}$	−0.021
	(0.010)	(0.013)	(0.013)
Post-Cert. 12-24 Mos. × Organic	−0.019$^{\cdot}$	−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 7: 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 8: 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 9: 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

Table 10: 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 11: Full Model Results

Variable	Means	StDev	Intxn with Demographic Vars			
	β	σ	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]	2.609	8.995		7.075	
	(1.228)					
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 12: 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 12 – 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 13: 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
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

Continued...

Table 13 – continued from previous page

Brand	1: Complete Labeling				2: No Labeling			
	Market Share	Revenue	Profit	Profit Chg	Market Share	Revenue	Profit	Profit Chg
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
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 14: 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 16 and Equation 17, 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.

A Price Premium Estimation with Full Sample

As a robustness check, the regression specification in Equation 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 15 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 15 about here.]

Table 15: 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: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

B Additional Tables

Tables 16, 17, 18, 19, and 20 present median own- and cross-price elasticities for each of the 50 RTE cereal brands, across all 5,988 markets.

[Table 16 about here.]

[Table 17 about here.]

[Table 18 about here.]

[Table 19 about here.]

[Table 20 about here.]

Table 16: 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 17: 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 18: 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 19: 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 20: 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.

C 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).