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

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Abstract

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

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Contents

List of Figures

List of Tables

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

The Non-GMO Project began offering non-GMO certification and labeling in 2010 for food products that fall under a 0.9% threshold for GMO presence. Products that obtain the certification feature an easily recognizable label[1] on their packaging that reads, "Non-GMO Project Verified." The Non-GMO Project does not restrict the types of products that can be certified, which is to say that a product is eligible for certification regardless of whether or not it contains ingredients for which commercially produced GMO variants currently exists. Furthermore, organic products, which are prohibited from containing GMO ingredients based on the National Organic Program standards, are also eligible for certification. As such, the cost of certification can vary significantly depending the magnitude of product changes required (e.g., product reformulation, sourcing of new ingredients, etc.) to meet the non-GMO certification standard.

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

[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.

GMO food products using the Non-GMO Project Verified label. The estimation is carried out on a large sample of weekly, product-level retail point-of-sale data for 18 product categories from U.S. supermarkets from 2009 to 2014. The transaction data is coupled with a unique dataset from the Non-GMO Project that contains non-GMO certification dates for products throughout the label's history. I find no evidence of price premiums or changes to quantity sold for newly certified non-GMO food products. I then investigate 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.

The paper is structured as follows. Section 1 provides institutional details and discusses the literature on quality disclosure and labeling as well as previous empirical work on willingness-to-pay for non-GMO products. Section 2 describes the data sources I employ to implement this study. Section 3 presents the empirical model for the analysis of non-GMO price premiums and quantities sold, with accompanying results in Section 4. Section 5 explores alternative strategies firms may use to extract rent and pass the certification cost to consumers. Lastly, Section 6 offers concluding remarks as well as next steps to better understand firm behavior and consumer preferences.

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,

[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.

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. As of December 2015, nearly 35,000 products from over 1,900 brands use the label, accounting for over $13.5 billion in annual sales.

Twenty U.S. states introduced mandatory GMO labeling legislation in 2014, by which time mandatory GMO labeling laws had already been passed in Maine, Connecticut, and Vermont. The labeling laws in Maine and Connecticut contained trigger clauses that required additional states to pass similar laws before theirs would go into effect, but the Vermont law contained no such clause and became effective on July 1, 2016. In the meantime, Congress passed the National Bioengineered Food Disclosure Standard (2016), creating a national mandatory GMO labeling standard. The bill, which became law on July 29, 2016, preempts any mandatory state GMO labeling laws and calls for the creation of a federal labeling standard within two years of its enactment. Notably, the law allows food manufacturers a

[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).

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 access 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 method 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

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

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, 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

[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.

[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).

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 consumers to know which products are at risk of containing GMO ingredients, and this lack of understanding may provide an unfair marketing advantage to products with high-risk ingredients carrying the label; and (4) The organization believes that verifying low-risk products helps raise awareness and build consumer interest for non-GMO food products as a whole, which can help set norms as new GMO products are developed.

Usage of the Non-GMO Project Verified label has grown significantly over the past five years, with sales of labeled products in 2014 totaling $11 billion (Non-GMO Project 2014a). Figure 1 shows the monthly cumulative growth in products using the label by Organic status. The label launched with about 200 products in 2010 and includes over 15,000 products as of January 2015. Products using the label are close to evenly split between Organic and conventionally grown. Non-GMO Project Verified products span a wide range of product categories as well. Figure 2 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;

[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).

breads, grains, and beans; fruits and vegetables; and packaged/prepared foods, each of which comprises over 1,500 products.

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

1.3 Relevant Literature

The concept of a credence good was first discussed by Darby and Karni (1973) as an extension of search and experience goods (Nelson 1970). In the context of a vertically differentiated good[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 low-

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

est 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.

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

More recent studies tend to focus on the issue of GMO labeling more directly and attempt to quantify the effects of different labels. Onyango et al. (2006) uses a nationwide survey to analyze U.S. consumer's choice of cornflakes in five different labeling scenarios. They find that consumers place a 10% premium on food labeled as non-GMO and 6.5% discount on food labeled as GMO; but, interestingly, consumers also attach a 5% premium

[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).

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.

2 Data

2.1 Nielsen Retail Scanner and Consumer Panel Data

Because the Non-GMO Project Verified label has only been in use since 2010, and the majority of its growth has occurred from 2012 onward, it is crucial that this research is conducted with the most recent demand data available. The Nielsen Retail Scanner (Nielsen RMS) data obtained through the Chicago Kilts Center contains weekly purchase and pricing data from retail store point-of-sale systems for over 2.6 million UPCs. The data includes 35,000 retail stores across the U.S., representing over 90 major retail chains in 52 markets. It includes all 1,100 reported Nielsen product categories, which span 125 product groups and 10 departments. In addition to demand data, the dataset includes store demographics and product characteristics. Most importantly, the timeframe for the data is 2009 to 2014, so it is sufficiently current to address my research questions.

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

2.2 Non-GMO Project Data

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

2.3 Selection of Food Categories

For this analysis, I focus on 18 food product categories primarily consisting of snack foods, dry goods, and other processed foods. Table 1 presents summary statistics for each product category of the Nielsen Retail Scanner Data from 2009 to 2014. The decision to focus on these categories is based on common and distinct factors for each category. First, all 18 categories are comprised of a non-negligible share of Organic products. Because Organic products do not contain GMO ingredients, their presence ensures the existence of products that are eligible for non-GMO certification without reformulation within a given food category, and these products may serve as a reliable counterfactual to help identify the effect of non-GMO labeling. Additionally, each category exhibits good variation in non-GMO labeling over time and has exhaustive coverage in the Nielsen data, helping ensure that the empirical analysis will have reasonable identification power to provide meaningful results.

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

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

Figure 3 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. These figures also show 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.

3 Empirical Model

For each product category in the analysis, the Nielsen Retail Scanner Data contains weekly prices and quantities sold across the U.S. at the store and UPC level. For each estimation, I restrict the sample to products that obtained the Non-GMO Project Verified label between 2010 and 2014, with at least 6 months of sales data prior to being certified and 12 months of sales data after certification[12]. The rationale for this approach is based on two requirements. First, the empirical specification relies on pre- and post-treatment indicators that I construct using the product verification dates; therefore, it is critical that sufficient data exists before and after the labeling event to estimate the effect of the label on prices and quantities. Second, the sample needs to remain relatively stable to minimize the confounding effects of product entry and exit on the model estimates. Restricting the sample as I have done helps ensure both these conditions are met.[13]

[12]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.

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

3.1 Price Premium Regression Model

3.1.1 Main Specification

I use scanner data from 2009 to 2014 aggregated to the national level and calculate a sales-weighted price per ounce p_{jklt}, where j is a product UPC, k is a brand, 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,

$$\begin{aligned}\log(p_{jklt}) = \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt}\end{aligned} \tag{1}$$

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, brand, category, and week fixed effects, respectively; and ϵ_{jklt} is a random error term. To control for any potentially confounding brand- and category-level pricing decisions, I allow the weekly intercepts to vary across brand and category by including Week×Brand×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.

3.1.2 Organic Interaction

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

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

$$\begin{aligned}\log(p_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ & + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \psi_7 PRE612_{jklt} \times \mathrm{Org}_j \\ & + \psi_8 PRE06_{jklt} \times \mathrm{Org}_j + \psi_9 POST06_{jklt} \times \mathrm{Org}_j + \psi_{10} POST612_{jklt} \times \mathrm{Org}_j \\ & + \psi_{11} POST1224_{jklt} \times \mathrm{Org}_j + \psi_{12} POST24p_{jklt} \times \mathrm{Org}_j \\ & + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \qquad (2)\end{aligned}$$

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

3.2 Quantity Regression Model

Depending on market conditions, firms may not be able to extract a price premium by using the label; however, firms may use the non-GMO Project Verified label to capture market share from other products. To test for this possibility, I regress weekly product sales quantities on the treatment indicators using a specification similar to that used for the price premium regressions. I use scanner data from 2009 to 2014 aggregated to the national level and calculate weekly sales quantity q_{jklt},where j is a product UPC, k is a brand, 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,

$$\begin{aligned}\log(q_{jklt}) = {} & \psi_1 PRE612_{jklt} + \psi_2 PRE06_{jklt} + \psi_3 POST06_{jklt} + \psi_4 POST612_{jklt} \\ & + \psi_5 POST1224_{jklt} + \psi_6 POST24p_{jklt} + \xi_j + \xi_t \times \xi_k \times \xi_l + \epsilon_{jklt} \end{aligned} \tag{3}$$

where the treatment indicators are the same as in Equation 1; ξ_j is a product UPC fixed effect; and $\xi_t \times \xi_k \times \xi_l$ is a Week×Brand×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.

3.3 Identification

Each of the specifications introduced above includes fixed effects to control for unobserved heterogeneity across product UPC and week-brand-category. The product UPC fixed effect controls for unobserved differences in product attributes across UPCs. The week-brand-category fixed effects essentially create weekly intercepts to control for brand-category level pricing changes. Therefore, the identification strategy relies on variation in timing of non-GMO certification for UPCs within each brand-category. In other words, if every UPC for a brand-category is certified in the same week, the treatment effect cannot be identified. 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.

4 Results

4.1 Price Premiums

4.1.1 Main Results

Table 2 presents the price premium regression results based on the model specified in the Equation 1. 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[14]. In the second specification with UPC and Week×Brand 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×Brand fixed effect absorbs much of the significant negative treatment effect observed in the first specification suggests that firms may be engaging in brand-level pricing decisions that were biasing the previous results.

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

[14]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.

tive, 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 brand 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 2 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.

4.1.2 Organic Interaction Results

Table 3 presents the price premium regression results based on Equation 2 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×Brand fixed effects, respectively. The preferred specification in Column III employs the full suite of fixed effects from Equation 2. The progression of results across specifications is very similar to that presented in the previous section, with the Week×Brand fixed effect absorbing some brand-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.[15] 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.[16] Therefore, I cannot conclude that organic products command smaller price premiums for non-GMO certification than non-organic products.

4.2 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 4 presents results for the quantity regression estimates based on Equation 3. 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 brand-level marketing strategies, this specification will produce biased results. Once we control for Week×Brand 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

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

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

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.

5 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.

5.1 Timing of Certification

Figure 4 illustrates the number of months a non-GMO product is on the market prior to receiving the Non-GMO Project Verification. A negative value indicates that a product obtained Non-GMO Project Verification prior to appearing in the Nielsen retail scanner data. A significant portion of products in each food category (20% on average) receive certification before entering the market, suggesting that firms may use the label to facilitate new product development and increase product diversity, thereby exercising market power through second-degree price discrimination.

To delve more into Figure 4, Table 5 presents comparisons 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. For many product categories, the point estimates for average price of New Entry products exceeds that 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.

5.2 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.[17] 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

[17] 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.

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 6 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.

6 Conclusion

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

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

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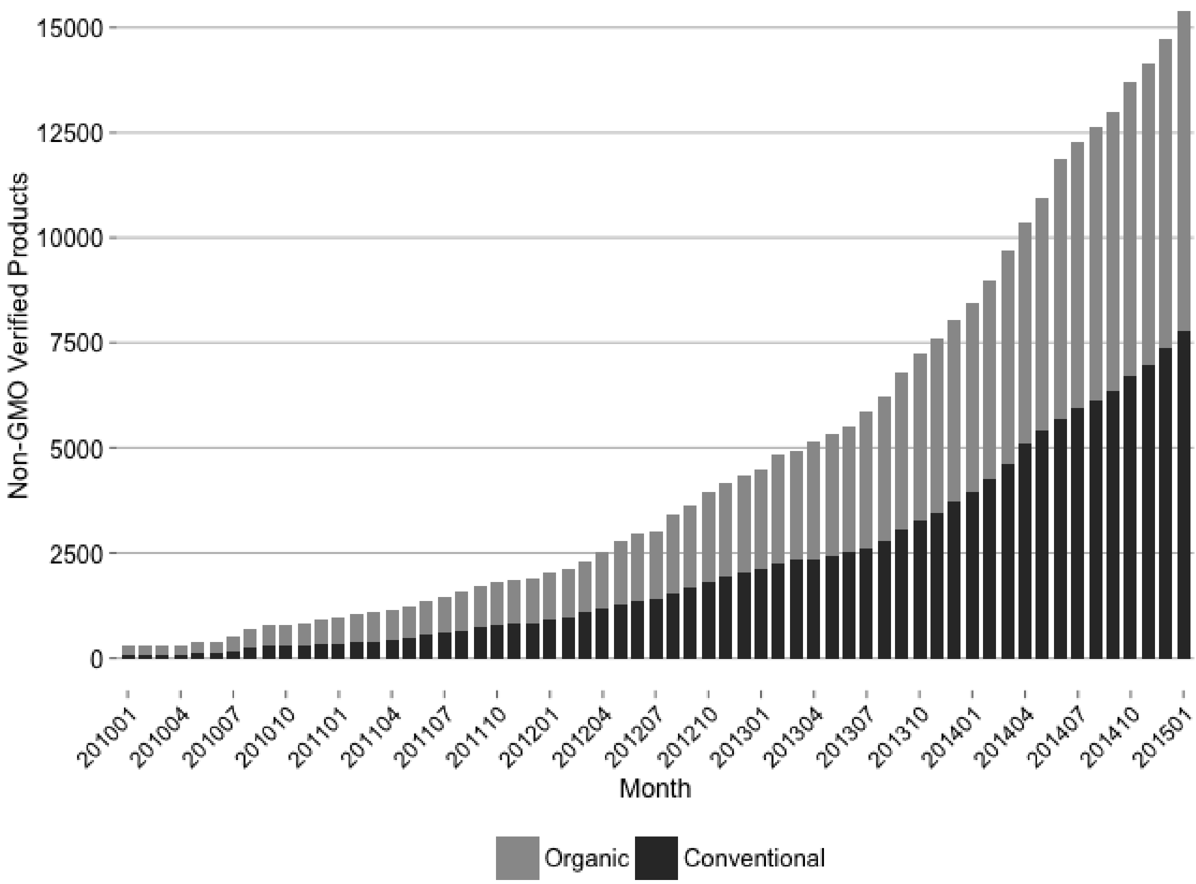
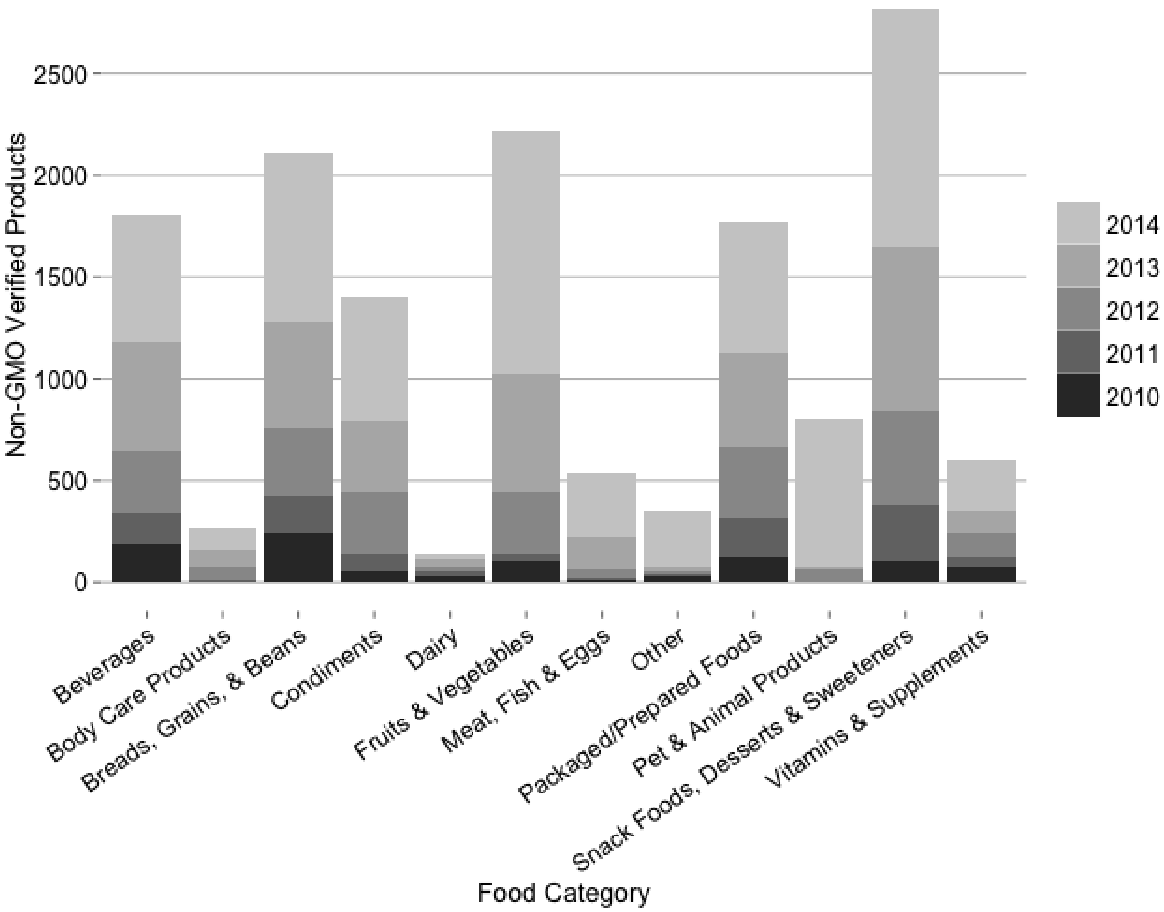


Note: Product counts are not unique by package specification.

Figure 1: Cumulative Monthly Non-GMO Project Verified Products by Organic Status



Note: Product counts are not unique by package specification.

Figure 2: Growth in Non-GMO Project Verified Products by Product Category

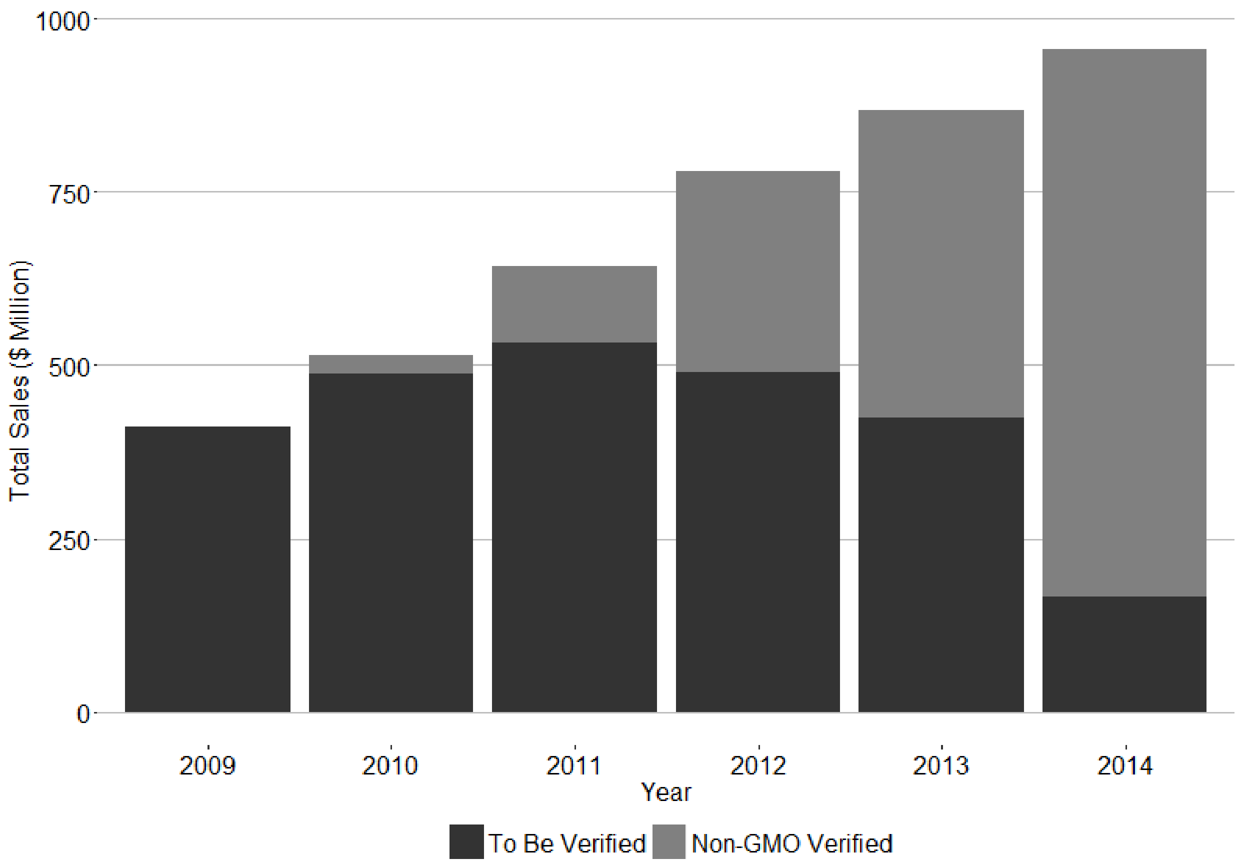
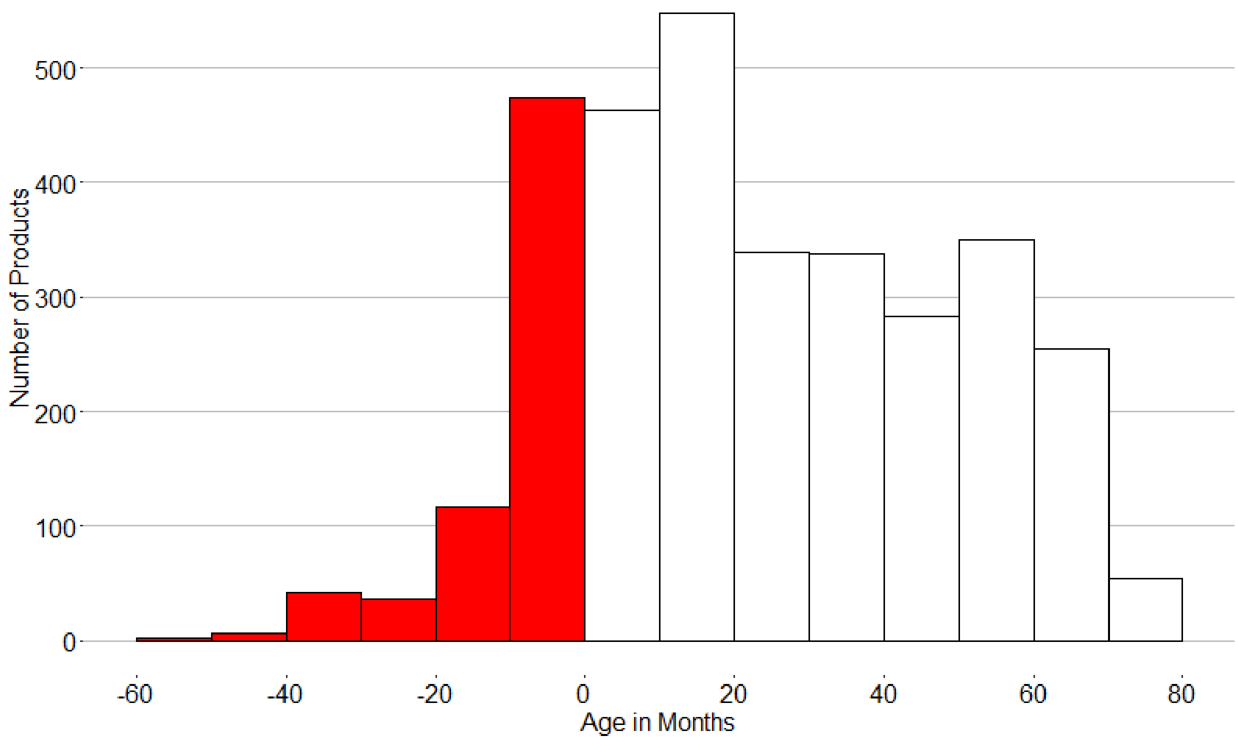


Figure 3: Annual Non-GMO Project Verified Product Sales



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

Figure 4: Product Age When Non-GMO Project Verified

Table 1: Summary Statistics

Product Category	Total UPCs	Brands	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 TYPES	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 2: 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
× Brand	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 3: 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
× Brand	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 4: 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
× Brand	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 5: Non-GMO Certification of New and Pre-Existing Food Products

Product	Mean Price ($/oz)		Total UPCs	
	New Entry	Pre-Existing	New Entry	Pre-Existing
BABY FOOD - STRAINED	0.41	0.30	57	81
CANDY-CHOCOLATE	0.77	0.87	46	67
NUTS - BAGS	0.62	0.58	30	85
SNACKS - POTATO CHIPS	0.35	0.33	31	83
CEREAL - GRANOLA & NATURAL TYPES	0.36	0.32	42	56
CEREAL - READY TO EAT	0.25	0.29	68	121
COOKIES	0.80	0.54	59	91
FRUIT-DRIED AND SNACKS	0.71	0.90	65	87
FRUIT DRINKS-OTHER CONTAINER	0.07	0.08	38	80
GRANOLA & YOGURT BARS	0.41	0.62	55	87
OLIVE OIL	0.33	0.44	12	24
PASTA-SPAGHETTI	0.27	0.24	14	19
RICE - PACKAGED AND BULK	0.12	0.19	52	73
SALAD AND COOKING OIL	0.40	0.54	25	52
SEASONING-DRY	2.30	0.66	26	228
SNACKS - TORTILLA CHIPS	0.18	0.28	25	84
TEA - BAGS	0.22	0.21	22	75
TEA - HERBAL BAGS	0.26	0.28	33	96

Table 6: 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

A Price Premium Estimation with Full Sample

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

Table A.1: Price Premium Regressions - Unrestricted Sample

	I	II	III
Pre-Cert. 6-12 Mos.	-0.007^{*}	-0.005	-0.006
	(0.003)	(0.004)	(0.005)
Pre-Cert. 0-6 Mos.	-0.002	0.001	0.000
	(0.003)	(0.005)	(0.006)
Post-Cert. 0-6 Mos	-0.002	-0.001	0.001
	(0.004)	(0.007)	(0.007)
Post-Cert. 6-12 Mos.	-0.001	-0.007	-0.003
	(0.004)	(0.007)	(0.008)
Post-Cert. 12-24 Mos.	-0.005	-0.009	-0.002
	(0.004)	(0.008)	(0.009)
Post-Cert. 24+ Mos.	0.007	0.000	0.012
	(0.005)	(0.011)	(0.012)
UPC FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
× Category	Yes	No	Yes
× Brand	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: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.