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The price of non-genetically modified (non-GM) food

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1. Introduction

Political action to bring about the mandatory labeling of genetically modified (GM) foods in the US escalated sharply in recent years, starting with several state ballot initiatives in the western part of the country. Despite overwhelming leads in early polls, statewide ballot initiatives in California in 2012, Washington in 2013, and Oregon in 2014 ultimately failed by narrow margins. Mandatory labeling advocates had some success, however, in persuading state legislatures.[1] In 2013, Connecticut and Maine passed mandatory labeling laws with contingency clauses (the laws would not go into effect until other neighboring states enacted similar labeling laws). Vermont became the first state to pass an unconditional mandatory labeling law in May 2014.

Demands for mandatory labeling were opposed by a number of stakeholders. Chief among these was a coalition of biotechnology and food firms that strongly opposed all such political initiatives and worked openly to defeat them at every level. In fact, a group of US and international food suppliers filed a lawsuit in the Second Circuit Court of Appeals to overturn Vermont's mandatory GM food labeling law on First Amendment grounds just weeks after its Governor signed the legislation into law. Opposition to labeling was broader, however, and individual scientists as well as scientific organizations, including the board of directors of the American Association for the Advancement of Science (AAAS, 2012), came out against the mandatory labeling of GM foods.

Throughout, the US Food and Drug Administration (FDA) steadfastly maintained its long-held position that GM foods would require labels only if they were unsafe or materially different from conventional foods. At the federal level, some sought to reinforce such a position. In March 2015 a bipartisan pair of lawmakers introduced a bill in the US House of Representatives, the Safe and Accurate Food Labeling Act of 2015, HR 1599, that would have barred states from imposing rules requiring GM labels, giving the FDA the sole authority to impose mandatory labeling. It passed four months later but the legislation stalled in the US Senate. In March 2016, a bipartisan compromise reshaped such considerations into the bill S.2609 to require a national standard of mandatory disclosure through quick-response (QR) codes, websites, on-pack labeling, and other means, with firms selecting the method of disclosure that works best for their products. This compromise bill ultimately became Public Law 114–216 in July 29, 2016. The Agricultural Marketing Service of the US Department of Agriculture is currently considering ways of implementing the law.

Throughout this period of ferment, the main argument for imposing mandatory GM labeling has been that consumers have the right to know what is in their food. However, there is no *prima facie* case that consumers have the right to know everything through mandated labels, that the right of consumers to know supersedes the right of producers to stay silent, or that such labels must be required at any cost. As such, the potential cost of mandatory GM labels and who must bear it became a flashpoint throughout the political debate in the US. Opponents of mandatory GM labeling argued that mandated GM labels would be costly and higher food prices would be paid by all consumers, even those who do not wish to avoid GM foods. In fact, in their complaint against Vermont the plaintiffs argued that, among other reasons, the state law is unconstitutional because "the State is forcing the costs of this experiment on out-of-state companies and citizens to which it is not politically accountable." Arguments about high costs and increased food prices have resonated with citizens. Analyses of the unsuccessful ballot initiatives in California and Washington indicated that voter concerns about potential food price increases figured in their defeat (Elway Poll, 2013; McFadden and Lusk, 2013). Proponents of mandatory GM labels have steadfastly maintained, however, that any incremental costs would be minimal ("the cost of ink").

Despite arguments on both sides of the debate, empirical evidence about the size of potential food price inflation from mandatory GM labeling in the US is scant, in part because quantifying it is inherently difficult. Much of the ultimate effect of mandatory labels depends on how food manufacturers, food retailers, and other food merchants would choose to act when the new law takes effect and GM ingredients must be disclosed. On the one hand, they could choose to maintain the current composition of their products, placing GM labels on them when necessary. On the other hand, they could choose to reformulate their products when necessary in order to avoid GM labels. This latter option,

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[1] Coalitions included consumer and environmental advocacy organizations as well as natural and organic food firms and producer associations (e.g. see http://www.vtrighttoknowgmos.org/who-we-are/).

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which is the one adopted by most European food manufacturers and retailers subjected to mandatory labeling laws, could be costly (Wesseler, 2014). In this paper we examine just how costly such reformulation might be for food suppliers and US consumers in the case of selected food products.

The labeling choices of food manufacturers and retailers are shaped by expectations of negative consumer response toward GM labels (Marchant et al., 2010), targeting of their products by political activists (Gruère and Rao, 2007), strategic behavior of competitors (Kalaitzandonakes and Bijman, 2003), and other factors. Given the complexity of these factors, correctly anticipating the responses of thousands of small, medium, and large food suppliers operating in the US with different product lines, manufacturing and distribution assets, supply chains, and sales in different regional and local markets is nearly impossible. Still, assuming that some food suppliers could reformulate their products to avoid GM labeling allows further insight into the potential costs of mandatory labeling. In order to assess how costly reformulation can be, we propose to use as measures the price premiums US consumers pay for non-GM and organic foods relative to conventional foods. In particular, we propose that, over time, such price premiums are largely shaped by the differences in the average costs of non-GM, organic, and conventional foods. As such they can provide effective *ex ante* estimates of the costs food suppliers would incur if they reformulated their products to avoid mandatory GM labels.

In order to test our propositions, we use hedonic modeling to estimate the retail price premiums consumers paid during the 2009–2016 period for non-GM and organic foods in four product categories: breakfast cereal, tortilla chips, salad and cooking oil, and ice cream. There are almost 11,000 ready-to-eat foods in our sample, 1350 of which are labeled as non-GM or organic. We selected these four product categories for their differences in the value shares of GM ingredients and hence their potential differences in reformulation costs. We show that the estimated price premiums for non-GM and organic foods in these four product categories are in line with the expected added costs for supplying such products. Based on this analysis, we draw conclusions about the potential food price increases that could occur if food manufacturers choose to reformulate their products using non-GM or organic ingredients in order to avoid mandatory GM labels.

2. The cost of change

Food manufacturers could avoid mandatory GM labels by replacing GM ingredients with ingredients from non-GM crops,[2] organic crops,[3] or crops that do not have GM varieties on the market (e.g., wheat or rice). Such changes could be difficult and costly to implement, particularly in the short run. For one, reformulation can alter the sensory and palatability characteristics of the final food product, so it may not always be possible to achieve identical product appearance and functionality using alternative ingredients. For another, non-GM and organic ingredients are generally more expensive.

Ingredients derived from non-GM and organic crops are more expensive in part because these crops have lower yields (e.g. Klümper and Qaim, 2014; Qaim and Zilberman, 2003; Seufert et al., 2012) and higher average production costs (Greene et al., 2009; Klümper and Qaim, 2014; McBride and Greene, 2015). Segregation costs are also incurred in order to keep these crops and their derivatives separate across the agrifood supply chain while various testing, certification, and traceability costs must be paid to demonstrate their authenticity when they are bought and sold (Kalaitzandonakes et al., 2001). Suppliers of non-GM and organic products are compensated for these higher costs through price premiums received from buyers (Kalaitzandonakes and Magnier, 2013; Varacca and Soregaroli, 2016). For instance, the prices received by US non-GM corn and soybean farmers in recent years have averaged 15% higher than the prices received by commodity corn and soybean farmers.[4] Likewise, the prices received by US organic corn and soybean farmers have, at times, been more than double the prices received by the commodity corn and soybean farmers (NASS, 2016).

Given that non-GM and organic ingredients are more expensive, the question we ask in this study is: how different would retail food prices be if food manufacturers reformulated their products and used such ingredients to avoid mandatory GM labels and differentiate through non-GM labels? Tracking how incremental costs incurred at the farm and throughout the supply chain trickle down to thousands of ready-to-eat non-GM and organic foods sold to consumers is an impossible task, not only because of the sheer number of products that must be analyzed but also because each product uses its own unique mix of ingredients with confidential recipes. Moreover, even if all incremental costs for replacing GM with non-GM or organic ingredients could somehow be calculated, they may still not provide sufficient insight. Indeed, little is known about the underlying demand conditions in these market segments. For instance, while there is some survey and experimental evidence of consumer willingness to pay for a few non-GM and organic foods in the US (e.g. Lusk et al., 2005), there is virtually no evidence how such stated willingness-to-pay translates into actual product purchases or how it shapes prices in these market segments. Given this lack of knowledge, it would be difficult to translate even dependable estimates of potential incremental costs into potential market outcomes.

3. The price premiums of non-GM foods and their determinants

To avoid some of the inherent measurement difficulties outlined above, we propose here to start at the retail end of the agrifood supply chain and work backwards. Retail price data should permit the estimation of any price premiums suppliers charge and consumers pay for non-GM and organic foods relative to conventional foods. Furthermore, such price premiums should reflect the underlying demand, supply (cost), and strategic pricing conditions in these market segments.[5]

Until now, there has been no systematic empirical evidence about the price premiums US consumers pay for non-GM foods relative to conventional equivalents. Here, we calculate such premiums for four carefully selected product categories: salad and cooking oil, breakfast cereal, tortilla chips, and ice cream. There are almost 11,000 branded products that are included in these four product categories (Table 1). We use monthly point-of-sale price data from AC Nielsen for all products that were sold in the US between 2009 and 2016.[6]

As Table 1 indicates, 1144 different salad and cooking oil products (UPCs), 1288 tortilla chip UPCs, 2227 breakfast cereal UPCs, and 5626

[2] Some crops (e.g. corn, soybeans, canola, and sugar beets) have both GM and non-GM varieties in the market. Some amounts of the non-GM varieties are segregated in their production, storage, shipping, and processing in order to avoid any admixtures from GM varieties. They are tested and traced across the agrifood supply chain so their non-GM status can be documented and certified at any point. All ingredients derived from such non-GM varieties are similarly segregated and identified throughout their supply chains. In this study we use the term "non-GM crops" to mean such segregated and certified non-GM crop varieties.

[3] Organic standards do not allow GM ingredients in organic foods. Like non-GM crops, organically produced crops are segregated and separately identified throughout their supply chain. Hence, organic crops and the ingredients derived from them are, by definition, also non-GM.

[4] According to USDA estimates, in 2017 92% of corn acres in the US were GM and 94% of all soybean acres were GM. Adoption of GM varieties in these and other crops has remained high for many years.

[5] To clarify terminology, we note here that conventional foods may or may not contain GM ingredients. The distinguishing feature of conventional foods, however, is that they do not specifically seek to use non-GM or organic ingredients and do not make claims of the absence of GM ingredients. By contrast, non-GM foods use segregated and traced non-GM and/or organic ingredients and declare the exclusion of GM ingredients through voluntary labels.

[6] AC Nielsen tracks of point-of-sale scanner data from a national sample of over 35,000 grocery, drug, mass merchandiser, and warehouse stores thought the US. The data includes UPC information, prices, quantities sold, promotions, and various product attributes. The data is collected both by store auditors and directly from food distributors.

Table 1
Product offerings (SKUs), market shares and growth in dollar sales for conventional, non-GM and organic products in selected product categories, 2009–2016.

	Conventional	Organic	Non-GM
Number of SKUs – 2016			
Salad and cooking oils	908	161	75
Tortilla chips	943	208	137
Breakfast cereal	1897	232	148
Ice cream	5237	162	227
Total	8985	763	587
Market share – 2016			
Salad and cooking oils	87.7%	9.9%	2.3%
Tortilla chips	89.0%	7.8%	3.2%
Breakfast cereal	91.7%	2.6%	5.7%
Ice cream	93.5%	0.9%	5.6%
Annual growth in sales – 2009–2016			
Salad and cooking oils	−2.0%	43.4%	12.5%
Tortilla chips	0.8%	8.4%	26.5%
Breakfast cereal	−3.9%	1.5%	36.2%
Ice cream	−0.9%	20.6%	4.5%

ice cream UPCs were sold in the US in 2016. There were a number of exits and entries of new products during the eight years of our analysis, but the total number of products did not change much in any of the product categories. A large number of these products were conventional, but there were almost 600 non-GM and more than 750 organic products sold in the US market in 2016. Non-GM salad and cooking oils, tortilla chips, breakfast cereals, and ice creams represented 2.3%, 3.2%, 5.7%, and 5.6% of total US sales in their respective product categories in 2016. Organic salad and cooking oils, tortilla chips, breakfast cereals, and ice creams represented, respectively, 9.9%, 7.8%, 2.6%, and 0.9% of total US sales in the corresponding product categories in 2016.

Table 2 presents the average price differences between non-GM/organic and conventional foods in the selected product categories over the eight year period, 2009–2016. The prices paid by US consumers for non-GM and organic products were significantly higher than those for conventional ones, but such price differences varied substantially across the four product categories. These price differences varied from month to month as well, but generally showed no significant trend over the period of the analysis. The question, then, is what factors might explain such price differences?

Economic theory suggests that in the short run the prices of goods are shaped by their marginal cost of production, consumer demand, and strategic pricing behavior when firms have market power. Along these lines, then, rising consumer demand for non-GM or organic foods may lift their retail prices, at least until demand growth levels off. Short term price increases may be more or less significant depending on how easily firms adjust their supplies of non-GM and organic products to meet changing market demand. In the presence of market power, suppliers of non-GM and organic products may inflate prices above marginal costs and short term price increases could be steeper. In the long run, however, with no barriers to entry and with enough time for firms to use production factors at their optimal levels, the prices of goods are largely determined by their minimum average costs (e.g. Mas-Colell et al., 1995). Firms that produce non-GM or organic foods incur higher production costs, and these costs should be reflected in their retail prices. In the long run, differences in the minimum average costs should largely determine the differences in the prices of non-GM and organic foods on the one hand and conventional foods on the other.

Table 2
Differences in market prices of organic and non-GM from conventional products.

	Price difference from conventional 2009–2016			
	Organic		Non-GM	
	Avg price difference	Std dev	Avg price difference	Std dev
Oils	41.61%	4.34%	56.29%	3.44%
Chips	26.26%	1.68%	38.02%	4.66%
Cereal	33.26%	5.58%	43.23%	3.85%
Ice cream	61.15%	1.97%	9.31%	3.82%

The so-called hedonic approach further posits that the prices of goods can be decomposed into the marginal implicit prices of the goods' attributes (Rosen, 1974). Although hedonic price analysis has been around for a long time (Waugh (1928) examined how vegetable prices varied with quality attributes), Rosen's conceptual foundation provided further meaning to the interpretation of marginal implicit prices. In particular, he showed that market forces would drive the marginal implicit prices to the point where the marginal cost of supplying an attribute equaled the marginal consumers' willingness-to-pay for the attribute. Later, Bajari and Benkard (2005) showed that the hedonic approach is applicable in conditions even beyond those posited by Rosen and that a hedonic price function exists even under imperfect competition.

The likelihood that sellers of non-GM and organic foods have market power that inflates prices above marginal costs is small. There are many sellers of non-GM and organic foods in the US and there is much competition among them and with sellers of conventional foods. Moreover, it is unclear what the barriers to entry are to prevent additional competition in selling non-GM and organic foods. Indeed, the presence of third party non-GM and organic certification schemes (e.g. Non-GMO Project Verified) makes it easier to enter the market, and such standardization can serve to commodify these attributes. Low barriers to entry, slack in non-GM acreage,[7] flexible acreage response by non-GM crop producers (Kalaitzandonakes and Magnier, 2016), and easy access to non-GM and organic ingredients through international trade would all seem to suggest that supply conditions in the non-GM and organic food markets could be rather elastic, even in the short run. Under these conditions, then, short term price increases due to growing market demand would be modest and short term price increases from market power unlikely, so price premiums for non-GM and organic foods relative to conventional foods should approximate the underlying differences in the minimum average costs for supplying these attributes.

4. Forming empirical hypotheses

Given these theoretical expectations, we selected the four product categories of foods described above specifically because of the differences in their underlying demand and supply conditions in order to test our propositions. First, consider the supply conditions of these products. On average, 60% of the wholesale price of salad and cooking oils goes to pay for the source crops (e.g. corn, soybeans, and canola) and their derivatives (e.g. crude oils), which are processed, refined, mixed, flavored, and bottled.[8] The crops used are largely GM, hence most conventional salad and cooking oils sold in the US are likely derived from such GM commodities. Given the large value share of GM crops and their derivatives in salad and cooking oils, procuring non-GM or organic ingredients to replace them could be quite costly. Such cost differences

[7] For instance, in 2016 there were more than 7.5 million acres planted with corn that was not GM in the US; most of such corn could be certified for use in the non-GM market. Of this, less than 220 thousand acres were planted with organic corn and less than 1 million acres were planted with certified non-GM corn, most of which was exported to Japan and S. Korea. As such, there is significant slack in acreage and production to increase the supply of non-GM corn and derivatives in the non-GM food market, as needed.

[8] The value shares for all four product categories used here are calculated with data from the US Census Bureau Manufacturing-Industry Series. The value shares are calculated as the ratio of the total expenses paid for primary agricultural commodities and derivatives by the manufacturers of the selected food products over the total value of their shipments. The relevant industries included here are oils refining & blending (NAICS 311225), tortilla manufacturing (NAICS 311830), breakfast cereal manufacturing (NAICS 311230), and ice cream and frozen dessert manufacturing (NAICS 311520). All value shares reported above are for 2012. Such value shares vary from year to year but their overall range remains similar across a number of years.

could cause the price premiums of non-GM and organic salad and cooking oils to be high.

For breakfast cereals and tortilla chips, we estimate that the average value shares of source crops and their derivatives (e.g. flours, meals, and grits) are 21% and 25%, respectively. Some of the crops used in breakfast cereal and tortilla manufacturing are GM while others (e.g. wheat, oats) do not have commercial GM varieties. As such, if breakfast cereal or tortilla manufacturers chose to reformulate their products they would need to source non-GM varieties for only some of the crops they currently use.[9] Given these lower value shares of GM crops and derivatives, the added costs for sourcing non-GM or organic ingredients to replace them is expected to be more moderate in breakfast cereal and tortilla manufacturing. Therefore the associated retail price premiums of non-GM and organic cereals and tortilla chips should also be moderate.

For ice cream products, the value share of crops and their derivatives (e.g. corn syrup) is small, on average less than 5%. When milk and its derivatives (e.g. casein, whey, and butter) are also included, the value share of primary agricultural commodities used in ice cream production increases to an estimated 30%. As a result, the added costs of using non-GM ingredients in ice cream production should be limited since the value share of GM crops and derivatives that must be replaced is small. The added costs of using organic ingredients in ice cream production could be much higher, however, as all primary agricultural commodities, including milk and derivatives, must be organic. For milk to be organic it must come from cows fed organic feeds – which can be quite costly.[10] As a result, the retail price premium of non-GM ice cream is expected to be low while the price premium for organic ice cream is expected to be higher.

The four selected product categories are also different in their underlying demand conditions, as the annual growth rates in sales and market shares of non-GM and organic products indicate (Table 1). Sales of non-GM tortilla chips and breakfast cereal grew at very high annual rates, 26.5% and 36.2% respectively, though from small bases. The growth in non-GM oils and ice cream sales was significant but more modest, 12.5% and 4.5%, respectively. Sales of organic salad and cooking oils and ice creams instead grew very fast, 43.4% and 20.6% respectively (Table 1). Organic tortilla chip and breakfast cereal sales grew at annual rates of 8.4% and 1.5%, respectively, over the 2009–2016 period. Fast sales growth in the absence of significant reductions in relative prices is taken as an indicator of high demand growth, which may cause the price premiums paid by consumers for such products to exceed the underlying increases in costs, at least in the short run.

Because all the products analyzed here are bundles of various attributes and claims (e.g. "organic", "no-gluten", "no preservatives", "natural", etc.) that can affect consumer demand and production costs, we use a hedonic price model to separate the price premiums for the non-GM and organic attributes from the price premiums paid for other attributes. This method has been used broadly for such measurements; Costanigro and McCluskey (2011) provide a recent overview of the method.

5. The hedonic price model

Hedonic price analysis is an econometric approach used to estimate how the prices of goods vary with the qualitative and quantitative attributes that characterize them. The theory underpinning this approach is Lancaster's (1966) utility theory which conceptualizes goods as bundles of attributes. As discussed above, the implicit price of an individual attribute arises from the equilibrium of producers' willingness to supply the attribute and buyers' willingness to spend some of their income to buy it. Although attributes themselves are not directly traded in the market, their implicit prices can be determined by examining how prices vary across goods with different attributes. The standard approach used in hedonic price analysis involves regressing the market price of the goods on their attributes.

Various functional forms can be used for the specification of hedonic price models, including linear function, semi-log function, and Box-Cox transformation. For this study, we chose the semi-log functional form; use of other functional forms yielded similar results. In particular, the hedonic price model that we used for our analysis is given by

$$\ln(Price_{it}) = \beta_0 + \beta_1 NonGM_i + \beta_2 Organic_i + \beta_3 Size_i + \beta_4 StoreBrand_i + \sum_{j=1}^{m} \gamma_j Attributes_{ij} + \sum_{k=1}^{3} \delta_k Quarter_{ik} + \theta Time\ trend_i + \varepsilon_{it},$$

where $Price_{it}$ is the average price of product (SKU) i in time period t, measured in \$/ounce, β, γ, δ, and θ are parameters to be estimated, and ε_{it} is a stochastic error term. *NonGM* and *Organic* take a value of 1 product i is, respectively, non-GM or organic.[11] *Size* is the weight of product i in ounces and *StoreBrand* indicates whether product i is a store brand owned by the supermarket selling the product or a manufacturer brand.

The set of variables *Attributes* corresponds to other characteristics of product i that may also influence its price and are specified as dummy variables. The attributes included in each hedonic price model differ according to the product category and hence the nature of the product. For salad and cooking oils, such product attributes included "natural", "rich in vitamins", "contains or rich in Omega 3", "rich in antioxidants" and "no preservatives." For breakfast cereal we considered the product attributes "natural", "multigrain", "whole grain", "gluten free" and "no preservatives." For tortilla chips we included the product attributes "natural", "multigrain", "gluten free" and "no preservatives." Finally, for the ice cream products we included the attributes "natural", "no hormones", "low fat or fat free" and "low calories."[12]

To capture any potential seasonal effects on product prices we used quarterly dummy variables. Using monthly dummy variables produced similar results; we maintained the quarterly dummies for parsimony. We also included a time trend in all models to capture any sustained trend in the average price of each product category over the period of analysis.

We also analyzed the potential impact of brand equity beyond the basic dichotomy of manufacturer brands and store brands. The data used in this study are unbalanced panel data with a time-series dimension and a cross-sectional (UPC) dimension. In order to account for the panel nature of our data, we consider two specifications of the one-way error components model with random effects. First, we consider a standard one-way random effects model in which an error variance component is estimated for each UPC in the data set. This version of the hedonic pricing model is estimated by feasible GLS with SAS. Second, because there may be dominant brands within each of these food markets, the product-level error components may be nested within a brand-specific error component. However, we cannot use the fully nested error components structure described in Chapter 3 by Baltagi

[9] For manufacturers considering reformulation with organic ingredients, however, all crops and their derivatives would need to be replaced with certified organic ones.

[10] For clarity, manufacturing non-GM ice cream does not require dairy ingredients to be produced from cows fed on non-GM feed. Livestock fed on GM feeds are not considered GMOs and their products are typically excluded from GM labeling. Organic ice cream, however, requires the use of dairy products produced from cows fed organic feeds.

[11] Most non-conventional products in our sample carry either an organic label or a non-GM label. There are also a few products that carry both organic and non-GM labels. Since all organic food products are also non-GM, whether explicitly labeled or not, we chose to categorize products carrying both organic and non-GM labels as "organic." Hence, in the standard formulation of our model all products that carried organic labels or *both* organic and non-GM labels were coded as 1 and were termed "organic." In order to test the robustness of our empirical models to this specification we also estimated all empirical models with an interaction term *organic * non-GM* so that all products that carried both organic and non-GM labels were separately accounted for. The results are reported in Tables 4–7 ("Models 2—organic * non-GM") and all empirical results are comparable with those in the base models.

[12] For consistency and parsimony, in our empirical base models we used 4–6 product attributes beyond the non-GM and organic attributes that are the focus of the study. The empirical results and conclusions do not change in any significant way when additional attributes are included in the models. We have estimated and present models with all available attributes in our data set in Tables 4–7 ("Models 4—Additional Attributes").

(2013). For this data set, many brands are only associated with one UPC, so we cannot separately estimate brand-level error components and the nested product-level error components for all UPCs. Moreover, some brands have been quicker to adopt certain product attributes like organic or non-GM, so the brand-specific error components may be correlated with some of the explanatory variables in the model and cannot be represented by random effects. For these reasons, we adopt a partially nested error components structure in which the brand-specific error components are limited to the top ten national brands. The brand-specific error components are represented by fixed effects (i.e., dummy variables), and the product-level error components remain as random effects. This mixed fixed-random error components structure is also described in Chapter 3 by Baltagi (2013).

All product prices were deflated by the Bureau of Labor Statistics Consumer Price Index (CPI). Estimates associated with continuous variables, such as the time trend, can be interpreted as the percentage effect on price associated with a one unit increase since the model is specified in the natural logarithm of price. For example, moving from time period $t = 1$ to $t = 2$ is associated with a $\theta * 100\%$ change in price. For binary variables, like *non-GM* or *Organic*, the percentage effects are calculated as $[\exp(\theta_1) - 1] * 100\%$. Hence, moving from a conventional to a non-GM product is associated with a $[\exp(\beta_1) - 1] * 100\%$ premium in retail price.

6. Empirical results

The empirical results from the estimated one way random effect model are reported in Tables 3 through 6.[13] With few exceptions, all parameter estimates in the four empirical models were statistically significant and carried the expected signs. Wald statistics indicated that all four models had significant explanatory power. All four product categories displayed quarterly seasonality in sales and the time trends implied small annual price increases or miniscule price declines. Hence, average prices for the four product categories examined here were stable for the 2009–2016 period.

For all four product categories we differentiated between store brands and manufacturer brands, and we distinguished the various products by the size of packaging. Both store brands and larger packs/sizes are typically associated with discounts. Store brands, on average, were sold at discounts, which varied from 16.4% (salad and cooking oil) to 27.5% (ice cream).[14] Discounts associated with larger sizes/packages were more modest and varied from less than 1.0% (salad and cooking oil) to 3.4% (tortilla chips).

The mixed effect models were estimated by adding the top 10 brands as explanatory variables in each of the one-way random effect models; the empirical results are reported in Tables 3–6 ("Models 3—top 10 brands"). Premiums or discounts were separately estimated for the top 10 brands but the rest of the structural parameter estimates were comparable to those derived in the base models. In the breakfast cereal market most of the top brands were premium brands priced 6–16% above the category average. In the salad and cooking oils market, the top selling brands were mostly discount brands priced 21% to 49% below the category average. In the tortilla chips and ice cream markets the top selling brands included both premium and discount brands, with the highest price premiums (more than 50%) commanded by prestige ice cream brands, like Häagen-Dazs and Ben and Jerry's. The distribution and relative size of price premiums and discounts associated with the top brands in the four product categories we analyzed reflect the degree of product differentiation and segmentation that characterize these four food markets.

We also examined how various product attributes and on-package claims shaped the retail prices consumers paid for the products in the four categories we analyzed. We found that products claiming to be "natural" commanded price premiums that varied from 10% (salad and cooking oils and breakfast cereal) to more than 36% (ice cream). "Gluten free" claims were associated with price premiums in all four product categories, from just over 10% (tortilla chips) to almost 40% (breakfast cereal). Product claims about the grain varieties used (e.g. "multigrain" or "whole grain") were associated with price premiums of almost 7% in breakfast cereal and 25% in tortilla chips. In the case of ice cream, product claims of "low calories" were associated with price discounts of almost 20% while "no hormones" claims were associated with price premiums of 15%. In contrast, "no preservative", "rich in antioxidants", "rich in vitamins", "fat free", "low fat", "low salt/sodium", or "low sugar/no sugar added" product claims were not associated with any significant price premiums in the four product categories we examined.

Our primary interest in this study was to estimate the price premiums consumers paid for non-GM and organic foods relative to their conventional counterparts and we summarize those premiums in Table 7 for ease of exposition. We report the price premiums we estimated from our base models but all other empirical models yielded similar estimates (see Tables 3–6). The average price premiums for non-GM salad and cooking oils, tortilla chips, breakfast cereals, and ice cream over their conventional counterparts were 61.8%, 24.3%, 26.3%, and 9.8%, respectively.[15] The relative size of these price premiums in all four product categories are therefore in line with the value shares of the primary agricultural commodities that would need to be replaced by non-GM ingredients and, hence, with the expected added costs for sourcing non-GM ingredients. The estimated price premiums for organic salad and cooking oils, tortilla chips, breakfast cereal, and ice cream over their conventional counterparts were 90.5%, 13.4%, 22.8%, and 38.9%, respectively. Once again, the relative sizes of these estimated price premiums are in line with the value shares of the primary agricultural commodities that would need to be replaced by organic ones and, hence, with the expected added costs for sourcing organic ingredients.[16] It is worth emphasizing the difference in the estimated price premiums of non-GM and organic ice cream (9.8% and 38.9% respectively), which presumably reflects underlying differences in the added costs implied by the two different attributes.

We also evaluated the stability of the estimates for non-GM and organic price premiums over the 2009–2016 period. As we have

[13] The TSCSREG SAS procedure was used for the empirical estimation of the unbalanced panel model (https://support.sas.com/documentation/onlinedoc/ets/132/tscsreg.pdf).

[14] All store brands are reported as a uniform product category by AC Nielsen and as such we cannot separate high quality store brands (e.g. Whole Foods) from discount store brands.

[15] We note that for the estimation of the salad and cooking oils models we present here we excluded oils that are derived from oilseeds that have no GM varieties in the market (e.g. olive, grapeseed, sesame, etc.). Some suppliers voluntarily label such oils as non-GM. Under FDA rules, non-GM claims for oils from oilseeds with no GM varieties in the market are considered misleading and are not allowed but this rule is not currently enforced. To evaluate the robustness of our empirical results, we also estimated all salad and cooking oil models (reported in Table 3) using the entire data set where all salad and cooking oil products were included. The estimated non-GM and organic price premiums from these empirical models were comparable to those reported in Table 3 (63% and 77% respectively). When we added a dummy variable that indicated whether an oil product was derived from oilseeds with no GM varieties in the market and we interacted this variable with the *non-GM* and *Organic* variables to evaluate if the implied price premiums were affected by the choice of ingredients we found that the price premiums for non-GM and organic salad and cooking oils from oilseeds with GM varieties (e.g. soybeans, canola, corn, etc.) were roughly 20–25% higher to those from oilseeds without GM varieties in the market. This result is in agreement with the hypothesis that price premiums for non-GM attributes are shaped by the added costs for supply them.

[16] Note that the non-GM price premiums for tortilla chips and breakfast cereal are higher than the organic price premiums for these two product categories. We generally expect the added costs and hence the associated price premiums of organics to be higher than those of non-GM foods in any product category. This may not, however, hold under all circumstances. Organic standards are process based while non-GM standards are quantitative (e.g. they required specific purity thresholds) and involve analytical testing. As such, the choice of specific standards and certification protocols can affect the added costs (e.g. Giannakas et al., 2011; Kalaitzandonakes and Magnier, 2013) and hence the implied price premiums. It is therefore possible that foods produced with non-GM ingredients subject to low purity thresholds and other strict production and supply chain requirements could experience higher added costs and imply higher price premiums than foods with organic ingredients which are based on less costly process standards.

Table 3
Alternative hedonic pricing models – salad and cooking oils.

	Model 1 (base model)				Model 2 (organic * non-GM)				Model 3 (top 10 brands)				Model 4 (additional attributes)			
Variable	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium
Intercept	0.891	0.042	21.21		0.891	0.042	21.21		0.988	0.046	21.570		0.890	0.042	21.02	
Non-GM	0.481	0.206	2.34	61.84	0.482	0.206	2.35	62.00	0.422	0.206	2.050	52.443	0.488	0.206	2.37	62.89
Organic	0.644	0.150	4.30	90.46	0.595	0.178	3.35	81.25	0.646	0.171	3.780	90.851	0.639	0.151	4.24	89.44
Natural	0.099	0.069	1.44	10.38	0.097	0.069	1.41	10.14	0.049	0.070	0.700	5.008	0.094	0.069	1.37	9.89
Size	−0.004	0.000	−13.03	−0.35	−0.004	0.000	−13.03	−0.35	−0.004	0.000	−13.300	−0.360	−0.004	0.000	−12.90	−0.35
Store Brand	−0.179	0.058	−3.06	−16.36	−0.177	0.059	−3.02	−16.21	−0.260	0.061	−4.290	−22.899	−0.182	0.059	−3.09	−16.65
Rich in vitamins	−0.091	0.171	−0.53	−8.70	−0.095	0.172	−0.55	−9.07	−0.083	0.176	−0.470	−7.943	−0.098	0.172	−0.57	−9.32
Rich in/contains Omega 3	−0.275	0.135	−2.04	−24.05	−0.277	0.135	−2.05	−24.21	−0.320	0.136	−2.360	−27.366	−0.268	0.135	−1.98	−23.53
Rich in antioxidants	0.403	0.428	0.94	49.65	0.408	0.428	0.95	50.40	0.283	0.560	0.510	32.721	0.420	0.430	0.98	52.16
No preservatives	−0.063	0.098	−0.64	−6.09	−0.063	0.098	−0.65	−6.11	−0.077	0.099	−0.770	−7.381	−0.086	0.098	−0.87	−8.22
Quater 2	−0.003	0.002	−1.84	−0.35	−0.003	0.002	−1.84	−0.35	−0.003	0.002	−1.840	−0.346	−0.003	0.002	−1.84	−0.35
Quater 3	0.007	0.002	3.58	0.66	0.007	0.002	3.58	0.66	0.007	0.002	3.580	0.660	0.007	0.002	3.58	0.66
Quater 4	−0.003	0.002	−1.54	−0.29	−0.003	0.002	−1.54	−0.29	−0.003	0.002	−1.540	−0.286	−0.003	0.002	−1.54	−0.29
Time Trend	−0.001	0.000	−33.87	−0.09	−0.001	0.000	−33.87	−0.09	−0.001	0.000	−33.880	−0.092	−0.001	0.000	−33.88	−0.09
Organic * Non-GM					0.752	0.256	2.94	112.12								
Brand1									−0.491	0.142	−3.46	−38.77				
Brand2									−0.456	0.169	−2.70	−36.64				
Brand3									−0.240	0.139	−1.72	−21.33				
Brand4									−0.553	0.194	−2.85	−42.45				
Brand5									0.037	0.324	0.11	3.75				
Brand6									−0.679	0.264	−2.57	−49.30				
Brand7									0.072	0.616	0.12	7.51				
Brand8									−0.234	0.555	−0.42	−20.87				
Brand9									0.045	0.575	0.08	4.65				
Low fat/fat free													−0.084	0.199	−0.42	−8.08
Fruit presence													1.499	0.567	2.64	347.53
Gluten free													0.229	0.226	1.01	25.75
Low salt or sodium													−0.053	0.150	−0.35	−5.15

Table 4
Alternative hedonic pricing models – tortilla chips.

	Model 1 (base model)				Model 2 (organic * non-GM)				Model 3 (top 10 brands)				Model 4 (additional attributes)			
Variable	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium
Intercept	1.762	0.111	15.85		1.763	0.111	15.86		1.646	0.112	14.72		1.760	0.111	15.81	
Non-GM	0.218	0.039	5.52	24.30	0.221	0.040	5.59	24.71	0.232	0.040	5.86	26.09	0.212	0.040	5.29	23.59
Organic	0.126	0.031	4.08	13.42	0.096	0.039	2.46	10.09	0.126	0.032	3.9	13.38	0.123	0.032	3.86	13.07
Natural	0.162	0.026	6.14	17.57	0.162	0.026	6.16	17.63	0.196	0.027	7.28	21.63	0.156	0.027	5.78	16.88
Packaging-bag	−0.142	0.110	−1.28	−13.21	−0.143	0.110	−1.30	−13.34	−0.096	0.111	−0.87	−9.13	−0.143	0.110	−1.3	−13.33
Size	−0.034	0.001	−30.39	−3.39	−0.034	0.001	−30.40	−3.39	−0.033	0.001	−28.2	−3.22	−0.034	0.001	−30.07	−3.37
Store Brand	−0.246	0.022	−11.18	−21.79	−0.241	0.022	−10.83	−21.44	−0.209	0.023	−9.15	−18.86	−0.243	0.022	−10.95	−21.61
Multigrain	0.219	0.041	5.36	24.53	0.220	0.041	5.37	24.63	0.209	0.041	5.05	23.22	0.204	0.042	4.9	22.67
Gluten free	0.097	0.025	3.95	10.24	0.094	0.025	3.80	9.90	0.117	0.025	4.69	12.40	0.100	0.025	3.97	10.54
No preservatives	0.044	0.023	1.87	4.46	0.042	0.023	1.78	4.25	0.039	0.024	1.62	3.94	0.042	0.025	1.72	4.30
Quater 2	0.006	0.001	4.92	0.56	0.006	0.001	4.92	0.56	0.006	0.001	4.93	0.56	0.006	0.001	4.92	0.56
Quater 3	0.010	0.001	9.21	1.02	0.010	0.001	9.21	1.02	0.010	0.001	9.22	1.02	0.010	0.001	9.21	1.02
Quater 4	0.018	0.001	15.74	1.77	0.018	0.001	15.74	1.77	0.018	0.001	15.75	1.77	0.018	0.001	15.74	1.77
Period	−0.0003	0.000	−18.70	−0.03	−0.0003	0.000	−18.71	−0.03	−0.0003	0.000	−18.71	−0.03	−0.0003	0.000	−18.69	−0.03
Organic * Non-GM					0.154	0.038	4.04	16.60								
Brand1									0.270	0.032	8.5	30.98				
Brand2									0.210	0.054	3.88	23.41				
Brand3									0.294	0.105	2.79	34.21				
Brand4									−0.212	0.087	−2.44	−19.13				
Brand5									0.119	0.196	0.61	12.66				
Brand6									−0.059	0.060	−0.98	−5.69				
Brand7									0.031	0.061	0.5	3.13				
Brand8									0.092	0.080	1.15	9.59				
Brand9									−0.310	0.152	−2.05	−26.66				
Calorie claim													0.251	0.171	1.47	28.55
Reduced cholesterol													−0.027	0.029	−0.94	−2.66
Low fat/fat free													0.011	0.035	0.31	1.10
Fiber presence													0.124	0.059	2.11	13.19
Fruit presence													0.014	0.050	0.28	1.39
Free of monosodium glutamate													−0.013	0.046	−0.27	−1.25
Abscence of specific oil													0.046	0.045	1.04	4.76
Low salt or sodium													−0.006	0.035	−0.17	−0.57

Table 5
Alternative Hedonic Pricing Models – Breakfast Cereal.

	Model 1 (base model)				Model 2 (organic * non-GM)				Model 3 (top 10 brands)				Model 4 (additional attributes)			
Variable	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium
Intercept	1.531	0.023	66.11		1.533	0.023	66.15		1.529	0.023	65.77		1.545	0.024	64.17	
Non-GM	0.234	0.037	6.32	26.31	0.237	0.037	6.42	26.77	0.238	0.037	6.43	26.83	0.193	0.038	5.1	21.32
Organic	0.206	0.030	6.81	22.82	0.166	0.035	4.78	18.10	0.207	0.030	6.85	22.97	0.174	0.031	5.52	18.96
Natural	0.102	0.026	3.87	10.70	0.101	0.026	3.83	10.59	0.114	0.026	4.30	12.03	0.087	0.027	3.17	9.05
MultigrainG	0.065	0.018	3.62	6.69	0.064	0.018	3.57	6.59	0.062	0.018	3.35	6.35	0.048	0.018	2.67	4.94
Whole grain	0.063	0.014	4.66	6.48	0.062	0.014	4.58	6.38	0.054	0.014	3.86	5.52	0.055	0.014	4	5.66
Gluten free	0.335	0.030	11.17	39.74	0.324	0.030	10.67	38.23	0.338	0.030	11.26	40.14	0.348	0.031	11.32	41.55
No preservatives	0.011	0.030	0.37	1.10	0.010	0.030	0.34	1.02	0.014	0.030	0.48	1.42	0.043	0.032	1.33	4.37
Packaging-box	−0.054	0.016	−3.37	−5.27	−0.054	0.016	−3.38	−5.28	−0.061	0.016	−3.74	−5.87	−0.061	0.016	−3.75	−5.95
Size	−0.025	0.001	−31.46	−2.44	−0.025	0.001	−31.53	−2.45	−0.025	0.001	−31.4	−2.45	−0.024	0.001	−30.72	−2.40
Store Brand	−0.215	0.014	−15.12	−19.35	−0.214	0.014	−14.99	−19.23	−0.203	0.015	−13.88	−18.37	−0.211	0.015	−14.24	−18.99
Quater 2	0.005	0.001	5.18	0.48	0.005	0.001	5.18	0.48	0.005	0.001	5.19	0.48	0.005	0.001	5.18	0.48
Quater 3	0.005	0.001	5.96	0.53	0.005	0.001	5.96	0.53	0.005	0.001	5.96	0.53	0.005	0.001	5.96	0.53
Quater 4	0.012	0.001	13.36	1.22	0.012	0.001	13.36	1.22	0.012	0.001	13.36	1.22	0.012	0.001	13.36	1.22
Period	−0.001	0.000	−34.75	−0.05	−0.001	0.000	−34.77	−0.05	−0.001	0.000	−34.74	−0.05	−0.001	0.000	−34.71	−0.05
Organic * Non-GM					0.265	0.040	6.62	30.40								
Brand1									0.122	0.074	1.64	12.93				
Brand2									0.133	0.066	2.00	14.19				
Brand3									0.062	0.066	0.94	6.37				
Brand4									0.151	0.072	2.08	16.24				
Brand5									0.120	0.069	1.74	12.80				
Brand6									0.017	0.063	0.27	1.75				
Brand7									0.126	0.073	1.72	13.45				
Brand8									0.146	0.073	2.01	15.78				
Brand9									−0.042	0.103	−0.41	−4.15				
Antioxidants													0.076	0.061	1.26	7.91
Reduced cholesterol													−0.031	0.020	−1.56	−3.02
Low fat/fat free													−0.002	0.018	−0.14	−0.24
Fiber													0.012	0.018	0.63	1.17
Flax/hemp seed													0.069	0.048	1.44	7.19
Fortified													0.088	0.076	1.16	9.18
Fruit presence													0.108	0.019	5.82	11.39
Low glycemic													−0.061	0.169	−0.36	−5.92
HFCS free													−0.193	0.030	−6.55	−17.55
Iron presence													0.007	0.029	0.25	0.73
Abscence of specific oil													−0.010	0.057	−0.18	−1.03
Protein claim													0.064	0.045	1.43	6.62
Low salt													0.018	0.032	0.55	1.80
Soy													−0.004	0.024	−0.19	−0.45
Less sugar													0.053	0.041	1.28	5.41
Rich in vitamins													−0.039	0.015	−2.57	−3.83

Table 6
Alternative hedonic pricing models – ice cream.

	Model 1 (base model)				Model 2 (organic * non-GM)				Model 3 (top 10 brands)				Model 4 (additional attributes)			
Variable	Estimate	Standard error	t value	Price premium	Estimate	Standard error	t value	Price premium	Estimate	Standard ERROR	t value	Price premium	Estimate	Standard error	t value	Price premium
Intercept	1.025	0.012	86.97		1.025	0.012	86.92		1.019596	0.0121	84.37		1.016	0.012	84.92	
Non-GM	0.093	0.031	3.00	9.77	0.093	0.031	2.99	9.75	0.084778	0.0311	2.72	8.85	0.091	0.031	2.94	9.57
Organic	0.329	0.045	7.23	38.92	0.356	0.049	7.33	42.82	0.384008	0.0467	8.23	46.82	0.319	0.046	7.01	37.56
Natural	0.314	0.032	9.78	36.84	0.317	0.032	9.87	37.30	0.249222	0.0344	7.24	28.30	0.313	0.032	9.77	36.80
Size	−0.013	0.000	−71.38	−1.29	−0.013	0.000	−71.38	−1.29	−0.01283	0.000184	−69.78	−1.27	−0.013	0.000	−70.45	−1.28
Store Brand	−0.322	0.013	−24.24	−27.53	−0.322	0.013	−24.22	−27.51	−0.32523	0.0134	−24.19	−27.76	−0.323	0.013	−24.26	−27.57
Hormone free	0.141	0.028	5.05	15.15	0.143	0.028	5.12	15.38	0.087406	0.0285	3.06	9.13	0.122	0.028	4.31	12.98
Low fat/fat free	0.001	0.026	0.03	0.07	0.002	0.026	0.09	0.24	−0.00826	0.0264	−0.31	−0.82	−0.007	0.027	−0.26	−0.68
Low calories	−0.203	0.030	−6.79	−18.39	−0.205	0.030	−6.83	−18.51	−0.18774	0.0303	−6.2	−17.12	−0.194	0.030	−6.47	−17.66
Quater 2	−0.016	0.001	−29.08	−1.56	−0.016	0.001	−29.08	−1.56	−0.01576	0.000542	−29.08	−1.56	−0.016	0.001	−29.08	−1.56
Quater 3	−0.023	0.001	−44.28	−2.31	−0.023	0.001	−44.28	−2.31	−0.02337	0.000528	−44.28	−2.31	−0.023	0.001	−44.28	−2.31
Quater 4	−0.011	0.001	−20.32	−1.08	−0.011	0.001	−20.32	−1.08	−0.01086	0.000534	−20.32	−1.08	−0.011	0.001	−20.32	−1.08
Period	0.002	0.000	187.24	0.16	0.002	0.000	187.24	0.16	0.001569	8.38E−06	187.27	0.16	0.002	0.000	187.21	0.16
Organic * Non-GM					0.202	0.091	2.23	22.42								
Brand1									0.459	0.061	7.56	58.24				
Brand2									0.416	0.064	6.47	51.55				
Brand3									−0.042	0.188	−0.22	−4.07				
Brand4									−0.249	0.070	−3.55	−22.05				
Brand5									−0.364	0.065	−5.59	−30.49				
Brand6									−0.011	0.074	−0.15	−1.11				
Brand7									−0.216	0.070	−3.09	−19.39				
Brand8									0.326	0.089	3.64	38.50				
Brand9									−0.479	0.084	−5.73	−38.05				
Calorie claim													0.593	0.199	2.98	80.89
Gluten free													0.108	0.026	4.11	11.46
Less sugar/no sugar added													−0.057	0.065	−0.89	−5.56

Table 7
Estimated price premiums of non-GM and organic foods & average value shares of ingredients that must be substituted for conversion to non-GM and organic status.

	Non-GM		Organic	
	Average price premiums 2009–2016	Value share of source crops & derivatives, 2012	Average price premiums 2009–2016	Value share of source crops & derivatives, 2012
Salad and cooking oils	62%	60%	90%	60%
Tortilla chips	24%	25% <	13%	25% <
Breakfast cereal	26%	21% <	23%	21% <
Ice cream	10%	5% <	39%	30%

reasoned above, the price premiums of non-GM and organic foods over conventional ones are shaped by long term trends in their underlying costs and short term variations in their demand. To evaluate the temporal stability of the estimated price premiums, we estimated all empirical models reported in Tables 3 through 6 with added interaction terms between the *nonGM* dummy variable and the annual *Time Trend* as well as interactions of the *nonGM* dummy variable with individual dummy variables $Year_2$, through $Year_8$, one for each of the years in the 2010–2016 period. Statistically significant estimates for the $nonGM * Trend$ interaction term in any of the models would indicate that the estimated non-GM price premium had an increasing or decreasing linear trend over the period of analysis. Statistically significant parameter estimates for any of the $nonGM * Year_i$ interaction terms would indicate measurable short term deviations away from the average price premium and any trend. We used F-tests to evaluate the statistical significance of all parameter estimates for the $nonGM * Year_i$ variables, as a set, in all four empirical models. We report the estimated base models with such interaction terms in Table 8 but we note that all remaining models in Tables 3-6 yielded comparable results when similarly augmented.

The estimated parameters of the $nonGM * Trend$ variable were not statistically significant in any of the four empirical models, indicating that the estimated non-GM price premiums in the four product categories we examined experienced no significant trends during the 2009–2016 period. Furthermore, almost all of the $nonGM * Year_i$ terms in all four empirical models were also not statistically significant (Table 8). F-tests in all four empirical models indicated that the hypothesis that all $nonGM * Year_i$ coefficients, as a set, were equal to zero could not be rejected at conventional levels.[17] These results are consistent with the low variances in the price differences of conventional and non-GM foods observed in all four product categories (Table 2) and indicate that the non-GM price premiums were stable for the entire 8 year period we examined.

Non-GM price premiums were stable throughout the period of analysis despite significant year-to-year variations in demand. Consider, for instance, the product sales in the non-GM breakfast cereal market over the 2009–2016 period illustrated in Fig. 1. Product sales experienced strong growth over the period of analysis but there were significant year to year swings in sales (both positive and negative). Despite these short term variations, non-GM price premiums for breakfast cereal remained unaffected and stable around their average value. Similar short term variations in demand and stability in the price premiums were observed in the remaining three product categories we examined. The stability of the non-GM premiums around their average values for an extended period of time further supports the hypothesis that non-GM price premiums are shaped primarily by long term trends in added costs (which are expected to be relatively stable) rather than short term variations in demand (which are expected to be more erratic).

[17] We also tested the stability of the organic premiums in a fashion similar to that for non-GM foods and we found that they were also quite stable. We found no statistically significant trends or annual deviations from means.

7. Implications

The price premiums of non-GM and organic foods presented here are based on differences in market prices paid by consumers over an eight year time period across thousands of food products sold in the US. The large number of products and long price series provide for robust estimates that are not sensitive to new product introductions, commodity price movements, or other factors that may be subject to short term shocks. These conditions allow some confidence in interpreting the results. The empirical results are also robust in the specification of the empirical models, several of which have been presented here.

The estimated price premiums of non-GM and organic products are also consistent with broad underlying supply and demand conditions. High price premiums correspond to higher expected added costs for sourcing non-GM and organic ingredients, as standard economic theory would predict. Short term demand shifts seem to have a more limited impact on price premiums which remain stable around their means. These are important results because they provide some guidance on anticipating the factors that could shape non-GM and organic price premiums for other product categories and perhaps their relative size, in some broad terms.

Importantly, the estimated price premiums paid by US consumers over the 2009–2016 period, 9.8% to 61.8% for non-GM products and 13.8% to 91% for organic products in the four categories examined here, are orders of magnitude higher than those projected by economic impact analyses of proposed mandatory GM labeling produced in recent years (e.g. Alston and Sumner, 2012; Lesser, 2014; NEMC, 2013). Hence, if our estimates are representative of price premiums paid by consumers for non-GM and organic products in other product categories and many food manufacturers prefer to source certified non-GM or organic ingredients instead of using and disclosing GM ingredients in their products, the cost of reformulation to avoid mandatory disclosure rules could turn out to be quite significant. Of course, under any circumstances we expect that GM foods will also remain in the market and that their share will tend to increase as the costs of reformulation become larger.

Economic theory provides some additional insight on the direction that price premiums might move if a significant share of the prepared and ready-to-eat foods sold in supermarkets today were to require non-GM and organic ingredients. If economies of scale and scope in handling, tracing, and certifying larger volumes of non-GM and organic ingredients can be brought to bear, they could lead to a reduction in added costs and price premiums. It is difficult, however, to see how significant economies of this kind exist, given the inherent batch-like nature of non-GM and organic supply chains. Indeed, it is easier to anticipate how average costs could increase in the non-GM and organic food sectors as demand for certified non-GM and organic crops and derivatives might increase well beyond current levels. For instance, current non-GM premiums paid at the farm level reflect differences in costs and yields between GM and non-GM crops, but such gaps could grow if the relative yields and cost efficiency of GM crops continue to improve against those of non-GM and organic crops. The aggregate minimum average cost of all non-GM farmers could also increase if expanded used of non-GM ingredients required non-GM acres to grow

Table 8
Hedonic Pricing Models –Tests for Non-GM Price Premium Temporal Stability.

	Salad and Cooking Oils				Tortilla Chips				Breakfast Cereal				Ice Cream		
Variable	Estimate	t value	Price premium	Variable	Estimate	t value	Price premium	Variable	Estimate	t value	Price premium	Variable	Estimate	t value	Price premium
Intercept	0.891	21.19		Intercept	1.762	15.81		Intercept	1.532	66.09		Intercept	1.024	86.91	
Non-GM	0.499	2.42	64.70	Non − GM	0.226	5.68	25.34	Non − GM	0.234	6.27	26.35	Non − GM	0.104	3.32	10.94
Organic	0.651	4.33	91.70	Organic	0.132	4.25	14.08	Organic	0.206	6.80	22.86	Organic	0.332	7.3	39.33
Natural	0.099	1.44	10.41	Natural	0.162	6.12	17.57	Natural	0.102	3.87	10.71	Natural	0.314	9.8	36.92
Size	−0.004	−13.02	−0.35	Packaging − bag	−0.141	−1.28	−13.19	MultigrainG	0.065	3.62	6.68	Size	−0.013	−71.37	−1.29
Store Brand	−0.179	−3.06	−16.38	Size	−0.034	−30.3	−3.39	Whole grain	0.063	4.66	6.49	Store Brand	−0.322	−24.23	−27.52
Rich in vitamins	−0.091	−0.53	−8.70	Store Brand	−0.247	−11.18	−21.85	Gluten free	0.335	11.18	39.78	Hormone free	0.142	5.07	15.21
Rich in/contains Omega 3	−0.275	−2.03	−24.02	Multigrain	0.220	5.35	24.56	No preservatives	0.011	0.37	1.10	Low fat/fat free	0.001	0.04	0.09
Rich in antioxidants	0.403	0.94	49.62	Gluten free	0.098	3.94	10.26	Packaging − box	−0.054	−3.37	−5.28	Low calories	−0.204	−6.79	−18.41
No preservatives	−0.063	−0.64	−6.08	No preservatives	0.044	1.89	4.50	Size	−0.025	−31.45	−2.44				
								Store Brand	−0.215	−15.12	−19.36				
Quater 2	−0.003	−1.85		Quater 2	0.006	5.04		Quater 2	0.005	5.07		Quater 2	−0.016	−29.15	
Quater 3	0.007	3.53		Quater 3	0.010	9.14		Quater 3	0.005	5.66		Quater 3	−0.023	−44.13	
Quater 4	−0.003	−1.62		Quater 4	0.018	14.99		Quater 4	0.012	12.70		Quater 4	−0.011	−20.18	
Time Trend	−0.001	−33.51		Time Trend	0.000	−18.18		Time Trend	−0.001	−33.33		Time Trend	0.002	184.62	
Non-GM * Trend	0.001	0.92		Non − GM * Trend	0.000	0.15		Non − GM * Trend	0.000	0.50		Non − GM * Trend	0.000	−0.38	
Non-GM * Year2	−0.069	−2.98		Non − GM * Year2	−0.016	−2.77		Non − GM * Year2	−0.012	−1.67		Non − GM * Year2	−0.016	−3.25	
Non-GM * Year3	−0.059	−1.70		Non − GM * Year3	−0.042	−4.78		Non − GM * Year3	−0.012	−1.24		Non − GM * Year3	0.011	1.51	
Non-GM * Year4	−0.062	−1.29		Non − GM * Year4	−0.013	−1.09		Non − GM * Year4	−0.010	−0.73		Non − GM * Year4	0.003	0.28	
Non-GM * Year5	−0.091	−1.47		Non − GM * Year5	−0.008	−0.51		Non − GM * Year5	0.005	0.31		Non − GM * Year5	−0.012	−0.83	
Non-GM * Year6	−0.110	−1.45		Non − GM * Year6	−0.011	−0.57		Non − GM * Year6	−0.006	−0.26		Non − GM * Year6	−0.013	−0.77	
Non-GM * Year7	−0.099	−1.09		Non − GM * Year7	−0.011	−0.49		Non − GM * Year7	−0.021	−0.82		Non − GM * Year7	−0.011	−0.52	
Non-GM * Year8	−0.102	−1.00		Non − GM * Year8	−0.001	−0.05		Non − GM * Year8	−0.020	−0.70		Non − GM * Year8	−0.025	−1.09	

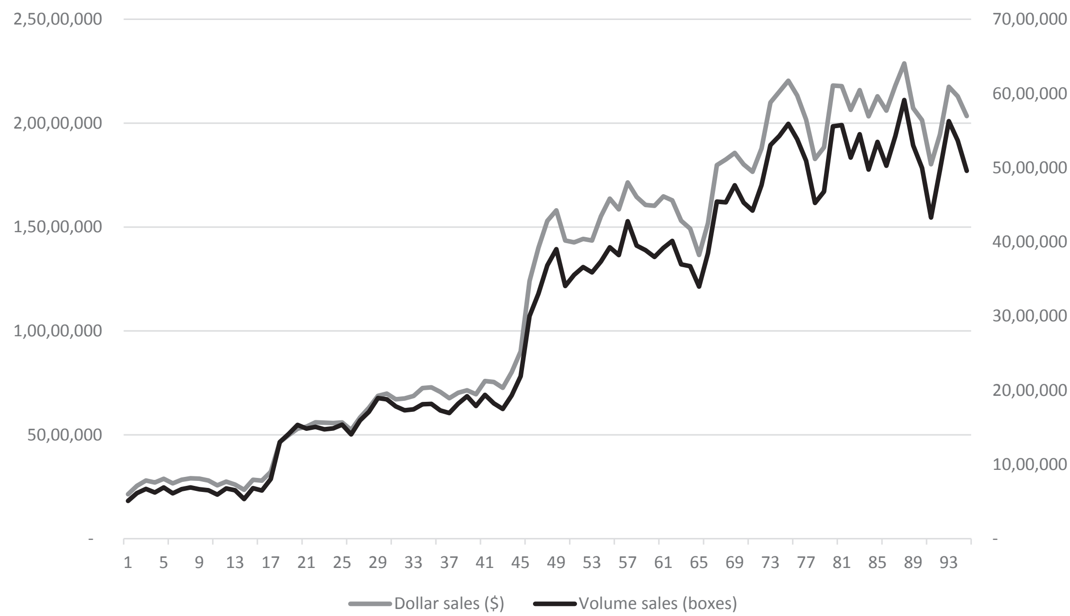

Fig. 1. Monthly volume and dollar sales of non-GM breakfast cereal in the US, 2009–2016.

significantly beyond their current levels. Farmers who produce non-GM and organic crops today are those who, because of experience, farm characteristics, and other such factors, are the lowest marginal cost producers (Kalaitzandonakes and Magnier, 2016). Significant expansion of non-GM production could attract less suitable acreage, management, and other farm resources, thereby leading to higher average minimum cost in the sector. Taken together, all such factors would suggest that dissipation of price premiums due to a possible expansion of non-GM and organic markets is unlikely.

Our estimated price premiums also reveal an important pattern that has generally been missed in the public debate about the cost of mandatory GM labeling and who may pay it. As we have reasoned and our empirical results have corroborated, price premiums tend to be higher for non-GM and organic foods for which primary agricultural commodities and their derivatives have a high value share. These are often low value-added foods that are purchased by consumers with lower incomes who prepare and eat most of the meals at home. This result suggests that greater attention on the distributional implications of mandatory labeling and the ensuing responses of manufacturers might be warranted.

It is also important to qualify the conditions under which our results can be representative. First, the ultimate scope of the GMO Disclosure and Labeling Law will be important as it will define which ingredients and foods will require labeling as well as the potential costs. For instance, we have estimated premiums for non-GM and organic salad and cooking oils but the USDA has not yet decided whether such products will require GM labels.[18] Second, while it is expected that manufacturers that source certified non-GM or organic ingredients will voluntarily label their products for these attributes, other manufacturers might seek to avoid mandatory GM labeling by sourcing, when possible, ingredients from crops that do not have GM varieties. The costs of such reformulations could be more moderate and the price premiums estimated here from voluntarily non-GM and organic labeled products might not be representative.

Perhaps the most important conclusion to be drawn from our results is that non-GM foods are more costly than GM foods, and policies that encourage food companies to shift toward non-GM ingredients are likely to increase food costs. Our results therefore suggest that there is a pressing need for further research in order to clarify the added costs consumers may have to pay under mandatory disclosure of GM ingredients and how such added costs might be distributed.

[18] USDA-ARS is currently considering whether highly refined oils or sugars that contain undetectable levels of GM material will require labeling.

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