The organic price premium: evidence from ready-to-eat cereal*

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Abstract

In this paper, I quantify the organic price premium in the ready-to-eat cereal industry. I estimate a random coefficient discrete choice demand model and use the implied demand elasticities, together with a supply-side pricing model, to recover product-level marginal costs and markups. This allows me to decompose the price difference between organic and non-organic cereals into cost and markup components. I find that organic cereals are more expensive primarily because they have higher marginal costs, not because firms charge higher markups on organic products. Counterfactual exercises that change the income distribution of consumers show that income heterogeneity does not explain the organic price premium. Overall, the results suggest that the organic premium reflects production-cost differences rather than price discrimination against consumers with a stronger willingness to pay for organic products.

Keywords: organic food, price discrimination, BLP, structural model

JEL classification: L13, D22, D43

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1 Introduction

The market for organic food has been growing rapidly in the past decades. In the United States, the sales of organic food were of \$76.6 billions in 2025, a growth of 6.8% compared to the previous year[1], and in the United Kingdom it rose to an all time high of £3.7bn in 2024.[2] There are several reasons to explain these numbers. One of them is that traditional retailers have recently started to offer this type of product, and thus consumers can buy them in their usual grocery shopping trip. Moreover, retailers are also offering their own brand of organic products (Jaenick and Carlson 2015). Another important reason is that organic products are seen as a healthier and environmentally friendly option. To be considered organic, products cannot use synthetic fertilizers, pesticides, and livestock feed additives during the production process.[3] Zepeda and Deal (2009) report that the health issue is the main reason for consumers to start purchasing organic products.[4]

An important characteristic of organic food products is that they are usually more expensive than their non-organic counterpart. Thompson and Kidwell (1998) and Jaenick and Carlson (2015) report a significant price premium for organic foods, with the former ranging from 40-175% and the latter from 45-70%. These premiums are large enough to attract the attention of policy makers. For example, The Economist reported that Turkey is subsidising the production of organic tea hoping that wealthy foreigners will then pay more for Turkish tea, and consequently increase the revenue of Turkish firms.[5]

Governments have also been urging households to eat healthier (Lan and Dobson 2017), and price is a key determinant of food choices. Therefore, understanding the determinants of organic price premiums is important both for firms and for

[1]Source: Organic Trade Organization. Their report can be obtained at https://ota.com/organic-market-report.

[2]Source:https://www.statista.com/topics/9070/organic-food-market-in-the-uk/.

[3]The Organic Trade Association reports that organic products reduce public health risk to farm-workers, their families, and consumers by minimizing their exposure to toxic and persistent chemicals. Source: https://ota.com/organic-101/health-benefits-organic

[4]On the other hand, the medical literature has not reached a conclusion if organic food is healthier or not. For a survey on this topic see, for example, Smith-Spangler et al. (2012).

[5]Source: https://www.economist.com/europe/2019/12/18/why-turkey-subsidises-organic-tea.

policy makers. A first explanation is that organic products are more costly to produce. Consistent with this mechanism, Mayen et al. (2010) find that American organic dairy farms are 13% less productive than non-organic ones, thus illustrating that organic production can involve higher costs.

A second explanation is that firms may charge higher markups on organic products if organic consumers have higher willingness to pay. The demand literature provides evidence that consumers value organic and health-related attributes. For example, Akgüngör et al. (2010) find that consumers are willing to pay more for organic food in urban Turkey, while Bonanno (2016) finds that consumers positively appraise the organic attribute in the yoghurt market. More broadly, Huang and Liu (2017) find that consumers buy more bottled water compared to other beverages when they receive more information about water health status, which is also documented by Batte et al. (2007) for the U.S. These papers motivate the possibility that firms could extract additional consumer surplus from products perceived as healthier or more environmentally friendly.

Therefore, it is important to determine whether the organic price premium reflects higher costs or higher markups, which is the empirical aim of this paper.

I study this question using data from the U.S. ready-to-eat cereal industry from 2008 until 2011 . I analyse this industry due to its importance for consumers. Cereal is the main breakfast food for most households in the United States. In 2019, 86.25% of the population consumed it.[6] Additionally, it is a industry that accounted for sales of 8.66 billion dollars in 2017.[7]

The most challenging issue in answering this question is that costs are not observable, and thus, a priori, I cannot know whether the price premium of organic food is due to higher markups or simply due to cost differences. To circumvent this problem, I use a discrete choice approach such as Berry (1994) and Berry et al. (1995). My model follows closely Cohen (2008). The demand side is modelled as a random coefficient model, and the estimation allows me to obtain the demand elasticities. Combining

[6] Source:https://www.statista.com/statistics/279999/us-households-consumption-of-breakfast-cereals-cold/

[7] Source: https://www.statista.com/statistics/407906/us-ready-to-eat-cereal-sales/

these elasticities with a supply side model, I recover the marginal costs and markups for each product. I then decompose the organic price premium into a marginal-cost component and a markup component.

I find that the organic price premium is mainly explained by higher marginal costs. Organic cereals are more expensive than non-organic cereals, but their markups are not higher. If anything, the estimated markup gap is slightly negative. This result is robust to alternative ways of measuring differential markups, including a counterfactual that removes the organic attribute from organic products and adjusts their marginal costs. I also use counterfactual income distributions to test whether firms charge higher organic markups in markets with richer consumers. The results imply that equalising income across consumers does not make the organic markup premium positive.

The study of price discrimination is well documented in the literature. For example, Cohen (2008) uses aggregate data to analyse price discrimination with respect to the size of the product in the paper towel market. He finds that quantity discounts are consistent with second degree price discrimination and that consumers are better off when it happens. The reason is that the use of this pricing strategy results into more competition in the multi-roll package size segment of the market.

Wallace (2018) analyses price discrimination in the U.S. fluid milk sector. Although it is also a good that consumers purchase in grocery stores, this market presents several other differences when compared to the cereal market. Milk is a more homogeneous good and the price of raw milk is regulated by the government, which implies that it is easier to obtain the costs for fluid milk. He found that retailers are only able to price discriminate on their own private label products, and that 7.2% of the mark-up can be explained by price discrimination, whereas for regional brands this number reduces to 0.34%.

One of the main issues regarding price discrimination has to do with its welfare consequences. Although firms use price discrimination to increase profits, its impact on consumers is, a priori, not clear. The reason is that price discrimination can induce consumers to switch, buying the product that gives them a higher utility, and this could generate an increase in consumer surplus. For instance, Leslie (2004) analyses a specific Broadway show, *Seven Guitars*, and finds that price discrimination allows firms to increase profits by 5%, and it has little or no effect on consumer welfare. On the other hand, Miller and Osborne (2014) find that price discrimination hurts consumers. They analyse the Portland cement industry in Arizona, California, and Nevada and estimate a structural model of spatial differentiation and price discrimination, finding that consumer surplus would increase by $30 million dollars per year if price discrimination was forbidden.

This paper contributes to this literature by showing that a large price premium need not imply higher markups. In this setting, the organic premium is better understood as a cost premium. This distinction matters because the policy implications are different. If high organic prices reflect costs rather than firms extracting additional surplus from high-willingness-to-pay consumers, then policies aimed at limiting markups would not address the main source of the price gap.

The remainder of the paper is organised as follows. Section 2 describes the data and the cereal industry. Section 3 describes the empirical model, Section 4 discusses the estimation strategy, and Section 5 presents the results. Section 6 presents a counterfactual and robustness exercises, and Section 7 concludes.

2 The Data and Industry

In this paper I use two different datasets to perform my analysis: the IRI Marketing Dataset[8] and the Consumer Population Survey (CPS) from the Bureau of Labour Statistics (BLS). From the IRI dataset I obtain information regarding prices, market shares, and products' characteristics, whilst from the CPS I obtain consumers' demographic characteristics.

The IRI dataset contains weekly store level data, for several Metropolitan Statistical Areas (MSAs) in the United States, and it provides prices, quantities, and some product characteristics. I aggregate this information to the quarterly level, for the period from 2008 until 2011, and define a market as the combination of MSA-quarter.

[8] see Bronnenberg et al. (2008) for a detailed description of this dataset.

I aggregate to the quarterly level for the following reasons. First, I need to observe products that were properly purchased during the period. Some products in the database are not purchased in a week or a month, but they all are purchased at least once in a quarter. This allows me to avoid the problem of zeroes in the market shares. Second, several costs components are determined for a period longer than a week or month. For example, marketing activities are planned at the quarterly level, and this is the same with some production decisions.[9]

I focus on 30 MSAs for which the CPS provides sufficient household coverage. Since the IRI data do not contain household demographics, I use CPS households to construct the distribution of consumer characteristics in each market. For each MSA-year, I randomly draw 200 households from the CPS and assign these draws to each quarter of the corresponding year. Thus, demographic characteristics vary across MSAs and years, while the same annual CPS draws are used for the four quarters within an MSA-year. From these draws, the main demographic variable used in the demand estimation is real household income per capita.

I study the ready-to-eat cereal category. Cereal is the main breakfast food for most households in the United States. In 2019, 86.25% of the population consumed it.[10] It contains many vitamins and it is also a good source of fibres and iron, which makes it a great choice to start the day.[11] It comes in different flavours, and with options for both adults and kids.

An important characteristic of this industry is the degree of concentration and the number of brands (Nevo 2001). Although there are many different products, the industry is highly concentrated. The four main firms and grocery stores' own brands are responsible for almost the whole market share in the period under analysis (see table 1).

The raw dataset has information on different types of cereals defined by their Universal Product Code (UPC), which is the definition of product used in the present

[9]See Nevo (2001) for the production process of ready-to-eat cereal.

[10]Source:https://www.statista.com/statistics/279999/us-households-consumption-of-breakfast-cereals-cold/

[11]For a better description of the industry see Nevo (2001) and references therein. Notice that these benefits can be reduced depending on the quantity of sugar in the cereal.

Table 1. Market Shares by Firm

Firm	Market share (%)	Volume (million oz.)
GENERAL MILLS INC	39.0	1636.8
KELLOGG CO	34.3	1438.2
PEPSICO INC	10.2	427.2
PRIVATE LABEL	9.8	411.3
RALCORP HOLDINGS	4.8	200.3
NATURES PATH FOODS INC	0.7	28.8
MCKEE FOODS CORPORATION	0.4	16.4
MOMS BEST NATURALS	0.1	5.1
BARBARA'S BAKERY	0.1	4.0
THE HAIN CELESTIAL GROUP INC	0.1	3.7
All other firms	0.5	22.3

Note: Market share is based on the total volume, measured in ounces, sold by grocery stores. Private Label refers to stores' own brands.

paper. I aggregate the weekly information to a quarterly level as follows: to obtain a quarterly price (measured in dollars per ounce), I average across all stores in the MSA and all weeks in the quarter.[12]

In my final analysis, I keep products that were available in at least one MSA for all sixteen quarters, and that had, at least, 0.001% market share in at least one market. In the end, I keep 750 products, and they account for 138,165 product-market observations, out of which 19,576 are of cereal produced with organic grains (14.17% of the total observations). Moreover, I only analyse cereals sold in boxes, because almost all observations belong to this category. From all the products, 64 correspond to cereal with organic grains; these are from nine national brands and from retail stores' own brands. Regarding the main brands, Kellogg's produces four organic cereals, General Mills produces 14, and the rest belong to smaller companies and retail brands.

An important definition in my analysis (see section 3 for more details) is the potential market of each product and I calculate it in a a way similar to Cohen (2008). I take the largest quarterly total sales from all products across the sixteen quarters as the potential market size for that MSA and multiply it by 4.[13] Then, the share of each

[12] Prices and household income are converted to real terms using regional CPI indices, with 1982-84 as the base period.

[13] Results are robust to other definitions, namely multiplying by 2, 3, or 5.

product is calculated by dividing the total sales (in ounces) of each product by the potential market size.

Regarding the product's characteristics, besides price, my main interest is on a dummy variable indicating if a cereal contains organic grains or not. The other two main variables are related to advertising activities of each product. IRI provides weekly display and feature information at the UPC-store level. The variable Feature is defined by IRI as follows: no feature, small size ad, medium size ad, large size ad, and a retailer coupon or rebate. I classify this variable in a scale of 0-4. Display is defined as no display, minor, and major, and I transform it into a scale of 0-2.[14] Both variables are aggregated to the quarterly level similarly to prices. Notice that, in the way I define these variables, they are representing the degree of in-store advertisement and describe the advertisement intensity (see Michel and Weiergraeber (2018) for the effects of advertisement intensity in prices).

The summary statistics are presented on Table 2. They show some clear patterns. As expected, organic cereal is, on average, more expensive, and has a lower market share than regular cereal. Regarding the advertisement variables, regular products are much more advertised than organic ones.

2.1 Price difference between organic and non-organic products

Table 2 shows that organic products are more expensive, on average, than regular ones. However, organic products differ from their non-organic counterparts not only in price but also in some other characteristics. In order to see if the price difference is due to observable characteristics, I run the following regression (in level and log):[15]

$$price_{jqm} = \lambda_1 \text{organic}_j + \lambda_2 \text{low sugar}_j + \lambda_3 \text{size}_j + \lambda_4 \text{feature}_{jt} + \lambda_5 \text{display}_{jt} + \eta_{b(j)} + \kappa_q + \nu_m + \epsilon, \tag{1}$$

[14] This is the information provided in the dataset. The only extra information given about the definition of feature and display is that major display includes end of aisle and code lobby, and small ad is usually one line of text.

[15] I use the observable characteristics available in the dataset.

Table 2. Descriptive Statistics

Statistic	Type	Mean	Std.	Min	Max
Panel A: Product characteristics					
Price ($/oz.)	Organic	0.151	0.040	0.024	0.347
	Regular	0.106	0.042	0.011	0.390
Size (oz.)	Organic	12.801	2.488	9.000	17.501
	Regular	15.348	4.340	0.810	48.000
Low Sugar	Organic	0.058	0.233	0.000	1.000
	Regular	0.104	0.306	0.000	1.000
Feature	Organic	0.136	0.254	0.000	3.000
	Regular	0.452	0.560	0.000	4.000
Display	Organic	0.060	0.137	0.000	2.000
	Regular	0.164	0.281	0.000	2.000
Share (%)	Organic	0.008	0.013	0.000	0.136
	Regular	0.059	0.088	0.000	1.404
Panel B: Consumer demographics					
Income ($)		14,918.61	16,704.76	0.09	791,777.61
Product-market observations			138,165		
Consumer draws			96,000		

Note: Price is measured in real dollars per ounce. Size is measured in ounces. Share is the product's market share in percentage points. Household income is measured in dollars in the CPS draws used for demand estimation.

where organic is defined as above, subindexes j stands for the product, q for the quarter, and m represents the MSA. η is a brand fixed effect, κ is a quarter fixed effect, ν is a MSA fixed effect, and ϵ is an error term.[16] Price is defined as price per ounce, size is the volume, in ounces, of the box, and low sugar is a dummy indicating that the cereal has low or zero sugar.

The results are presented in Table 3. They suggest that, even controlling for other observable characteristics, there is still a difference of 17.5% between the price of organic and non-organic products. However, this price premium could stem either from different production costs or from price discrimination. In the next Section, I proceed to disentangle these two factors.

Regarding the other variables, as expected, Table 3 shows that more advertised products are, per ounce, cheaper (for both measures of advertisement used). Additionally,

[16] The results remain the same if instead of using MSA and quarter fixed effects additively, I use them as a multiplicative market fixed effect.

it shows that the bigger the box of cereal, the lower is its unit price. Cereal with low sugar is also more than expensive than sugary ones.

Table 3. Conditional Price Difference Between Organic and Regular Products

Variable	Price	Log(price)
Organic	0.018***	0.175***
	(0.001)	(0.008)
Low Sugar	0.009***	0.053***
	(0.001)	(0.011)
Size (oz.)	-0.003***	-0.035***
	(0.000)	(0.001)
Feature	-0.011***	-0.099***
	(0.001)	(0.006)
Display	-0.012***	-0.124***
	(0.001)	(0.009)
Observations	138,165	138,165
MSA fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Brand fixed effects	Yes	Yes

Note: * denotes significance at 10%, ** at 5%, and *** at 1%. Standard errors are clustered at the MSA level.

3 Model

I use a discrete choice approach to analyse the possible existence of price discrimination. The choice for a structural model follows the arguments presented by Berry (1994). Although a reduced form approach is feasible to estimate demand elasticities, if there is a market with N products, then there are N^2 elasticities to estimate. A structural model allows the parametrisation of the consumer utility function and all those cross-price elasticities can be identified estimating fewer parameters. Finally, in this setting, it is easy to go from statements about aggregate demand to statements about consumer utility, which eases the welfare analysis. I use the well known random coefficient discrete choice approach - BLP - such as in Berry et al. (1995) and Nevo (2001). My approach follows closely Cohen (2008), and an advantage of this type of model is that it implies a very general substitution pattern among different products, and it does not suffer from the Independence of Irrelevant Alternatives

(IIA) critique that other types of discrete choice models do.

3.1 Demand

I observe $t = 1, \ldots, T$ markets, each with $i = 1, \ldots, I_t$ individuals. A market is defined as a quarter-MSA and, in each market, consumers have to choose among J products. Following the same notation as in Nevo (2000) and Nevo (2001), consumer's i utility of consuming product j in market t is expressed as

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_j + \Delta\xi_{jt} + \varepsilon_{ijt}, \tag{2}$$

where x_{jt} is a K-dimensional vector of observable characteristics of product j in market t, including the organic feature of this product. In the same way, p_{jt} is the price of product j in market t, ξ_j is the mean of the unobserved (to the econometrician) product characteristics, $\Delta\xi_{jt}$ is the market specific deviation from this mean, and ε_{ijt} is a mean zero stochastic term, which, as usual, is assumed to follow a type-I extreme-value distribution.

The individual specific coefficients, α_i and β_i, are

$$\begin{pmatrix} \beta_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta \\ \alpha \end{pmatrix} + \Pi D_i + \Sigma \nu_i, \tag{3}$$

where α and β are the mean taste parameters, D_i is a $d \times 1$ vector of observable demographic variables in market t, Π is a $(K+1) \times d$ matrix of coefficients that measure how the consumer taste characteristics vary with demographics characteristics, ν_i is a $K \times 1$ vector representing the unobserved random part of consumer taste, which is assumed to be $\nu_i \sim N(0, I_{k+1})$, and Σ is a $K \times K$ scaling matrix.

The utility from the outside good is

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 \nu_{i0} + \varepsilon_{i0t}. \tag{4}$$

As usual, since the mean utility of the outside good is not identified, ξ_0 is normalised to zero.[17]

Let $\theta = (\theta_1, \theta_2)$ be the vector that contains all the parameters of the model. The vector $\theta_1 = (\alpha, \beta)$ contains the linear parameters, and the vector $\theta_2 = (\Pi, \Sigma, \pi_0, \sigma_0)$ contains the non-linear parameters.[18] I can express equation (2) as a sum of mean utility, δ_{jt}, and a mean zero heteroskedastic deviation from the mean that captures the effects of random coefficients, $\mu_{ijt} + \varepsilon_{ijt}$. It can be expressed as

$$u_{ijt} = \delta_{jt}(x_{jt}, p_{jt}, \xi_j, \Delta\xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, \nu_i, D_i; \theta_2) + \varepsilon_{ijt}, \tag{5}$$

where $\delta_{jt} = x_{jt}\beta_i - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}$, and $\mu_{ijt} = [p_{jt}, x_{jt}]' * (\Pi D_i + \Sigma \nu_i)$, where $[p_{jt}, x_{jt}]$ is a $(K+1) \times 1$ vector.

Consumers purchase only the good that gives them the highest utility. To obtain the market shares of each j-th product, I have to sum up over the mass of consumers in each market, and they are given by the following expression:

$$s_{jt}(\delta_t, \theta_2) = \int_{D_i, \nu_i} \frac{exp\{\delta_{jt} + \mu_{ijt}(D_i, \nu_i; \theta_2)\}}{\sum_{k=0}^{J} exp\{\delta_{kt} + \mu_{ikt}(D_i, \nu_i; \theta_2)\}} dF(D_i, \nu_i; \theta_2). \tag{6}$$

From these results, I obtain the own-price elasticities, which are given by the following expression:

[17] Notice that π_0 and σ_0 are not identified separately from the coefficients of an individual-specific constant term in equation (2), so I also normalise them to zero.

[18] I can separate this way because the model generates a non-linear system of the market shares. Note that the non-observed products' characteristics enter the market share equation in a non-linear way.

$$e_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}}, \tag{7}$$

where s_{jt} is defined as above.

Due to the multidimensional integral in equation (6), an equation that is linear in the parameters cannot be obtained. Berry et al. (1995) proved that, given the parameter values and the observed market shares, this equation system is a contraction mapping in δ_t, and hence a unique vector can be obtained using iterations.

Notice that ξ_j, the non-observed product' characteristics, are related with prices, which generates the problem of simultaneity. Therefore, it is necessary to use instruments to estimate the demand system (in Section 4.3 I describe the instruments used.) In Section 4, I provide more details on the estimation procedure.

3.2 Supply

In order to recover the margins, I assume, as in Nevo (2001), that firms engage in differentiated products Bertrand-Nash competition. The profit maximisation problem for firm f in market t is as follows:

$$Max\, \Pi_{f_t} = \sum_{j \in F_{f_t}} (p_{jt} - mc_{jt}) M_t s_{jt}(\mathbf{p_t}), \tag{8}$$

where F_{f_t} is the subset of products that are produced by firm f in market t, which varies by firm and market, M_t is the potential size of market t, and $\mathbf{p_t}$ is a vector containing prices for all products in market t.

The first order condition is given by:

$$s_{jt}(\mathbf{p}_t) + \sum_{r \in F_f} (p_{rt} - mc_{rt}) \frac{\partial s_{rt}(\mathbf{p_t})}{\partial p_{jt}} = 0, \;\; j = 1, \ldots, J_t. \tag{9}$$

Let us define $S_{jrt} = -\frac{\partial s_{rt}(\mathbf{p_t})}{\partial p_{jt}}$, $j, r = 1, \ldots, J_t$. Additionally, let $\omega^*_{jrt} = 1$ if j and r are produced by the same firm, and $\omega^*_{jrt} = 0$ otherwise. ω^*_t is a $J_t \times J_t$ matrix with $\omega_{jrt} = \omega^*_{jrt} * S_{jrt}$. Thus, the set of the J_t first order conditions can be written as the following vector:

$$s_t(\mathbf{p_t}) - \omega_\mathbf{t}(\mathbf{p_t} - \mathbf{mc_t}) = \mathbf{0}. \tag{10}$$

From this equation, I can calculate the margins, $(p_t - mc_t)$, and from them, I can recover the marginal cost, which is

$$\mathbf{mc}_t = \mathbf{p}_t - \omega_t^{-1} * \mathbf{s}_t(\mathbf{p}_t). \tag{11}$$

3.3 Decomposing the organic premium

To decompose the organic price premium, I compare organic and non-organic products within each market. Since products differ substantially in their market shares, I use share-weighted averages within each group. For any variable x_{jt}, define the share-weighted average among organic products in market t as

$$\bar{x}_{ot} = \frac{\sum_{j=1}^{J_{ot}} s_{jt} x_{jt}}{\sum_{j=1}^{J_{ot}} s_{jt}}, \tag{12}$$

and the corresponding share-weighted average among non-organic products as

$$\bar{x}_{not} = \frac{\sum_{j=1}^{J_{not}} s_{jt} x_{jt}}{\sum_{j=1}^{J_{not}} s_{jt}}. \tag{13}$$

Using these averages, the organic price premium in market t can be written as

$$\bar{p}_{ot} - \bar{p}_{not} = (\overline{mc}_{ot} - \overline{mc}_{not}) + \left[\overline{(p - mc)}_{ot} - \overline{(p - mc)}_{not}\right]. \tag{14}$$

The first term captures the part of the organic price premium explained by differences in marginal costs. The second term captures the difference in margins between organic and non-organic products. I interpret this second term as the markup component of the organic price premium. Therefore, for each market t, I define

$$PD_t = \overline{(p - mc)}_{ot} - \overline{(p - mc)}_{not}. \tag{15}$$

The overall measure is the average across markets:

$$PD = \frac{1}{T}\sum_{t=1}^{T}\left[\overline{(p - mc)}_{ot} - \overline{(p - mc)}_{not}\right]. \tag{16}$$

I also report the share of the organic price premium accounted for by this markup component:

$$\text{Markup Share} = \frac{\frac{1}{T}\sum_{t=1}^{T}\left[\overline{(p - mc)}_{ot} - \overline{(p - mc)}_{not}\right]}{\frac{1}{T}\sum_{t=1}^{T}\left(\bar{p}_{ot} - \bar{p}_{not}\right)}. \tag{17}$$

This measure allows me to ask: are organic products priced with higher markups overall?

3.4 Organic-attribute counterfactual

The decomposition above measures whether organic products have higher markups than non-organic products in the observed equilibrium. As a robustness exercise, I also implement a counterfactual that is closer to a price-discrimination measure. In this exercise I ask whether the organic label itself, rather than the broader set of characteristics associated with organic products, generates higher markups.

I first define the baseline markup difference as

$$PD_{All} = \frac{1}{T}\sum_{t=1}^{T}\left[\overline{(p-mc)}_{ot} - \overline{(p-mc)}_{not}\right]. \tag{18}$$

This object is the share-weighted organic minus non-organic markup gap, averaged across markets. It captures all differences in markups between organic and non-organic products, including differences associated with characteristics other than the organic attribute.

To isolate the contribution of the organic attribute, I remove this attribute from originally organic products and solve again for equilibrium prices. Since the organic attribute may also affect production costs, I first estimate the organic component of marginal costs using

$$mc_{jt} = \lambda_0 + \lambda_1 o_j + w'_{jt}\lambda + \nu_m + \kappa_q + \epsilon_{jt}, \tag{19}$$

where o_j is an indicator equal to one if product j is organic, w_{jt} includes observed cost shifters such as size and sugar content, ν_m are MSA fixed effects, and κ_q are quarter fixed effects. The coefficient λ_1 measures the average marginal-cost premium associated with the organic attribute.

In the counterfactual, I subtract this cost premium from the marginal costs of originally organic products, so that $mc^{ex}_{jt} = mc_{jt} - \hat{\lambda}_1$ for organic products, while marginal costs for non-organic products are unchanged. On the demand side, I remove the organic attribute by setting the organic indicator to zero for originally organic products and by subtracting the mean utility contribution of the organic characteristic. I then solve the firms' first-order conditions again and obtain a new vector of equilibrium prices, $\mathbf{p}_t^{ex}$.

Using these counterfactual prices and marginal costs, I compute

$$PD_{Restricted} = \frac{1}{T}\sum_{t=1}^{T}\left[\overline{(p^{ex} - mc^{ex})}_{ot}^{ex} - \overline{(p^{ex} - mc)}_{not}^{ex}\right], \tag{20}$$

where the superscript *ex* indicates that the averages are computed using the counterfactual equilibrium. This object measures the markup difference that remains after removing the organic attribute and its estimated cost component. The price discrimination component associated with the organic attribute is then

$$PD = PD_{All} - PD_{Restricted}. \tag{21}$$

3.5 Income-distribution counterfactuals

I also use the estimated model to test whether the organic price premium is related to the income distribution of consumers. The demand estimates allow log income to affect both price sensitivity and the taste for the organic attribute. If firms charge higher markups for organic products because organic consumers are richer or less price sensitive, changing the income distribution should affect the organic markup premium.

In these counterfactuals, I hold marginal costs, observed product characteristics, and unobserved product quality fixed. I only change the log-income variable in the consumer draws and then solve again for the vector of Bertrand-Nash equilibrium prices, denoted by $\mathbf{p}_t^{cf}$. Given these prices, the counterfactual margin of product j in market t is

$$p_{jt}^{cf} - mc_{jt}. \tag{22}$$

I consider two income counterfactuals. In the first, all consumers within each MSA-quarter are assigned the mean log income of that market. This removes within-market income heterogeneity while preserving differences in average income across markets. In the second, all consumers in all markets are assigned the same national mean log income. This removes both within-market income heterogeneity and cross-market differences in average income.

For each counterfactual, I recompute the organic price premium, the organic marginal-cost premium, and the organic markup premium using the same share-weighted market-level averages defined above. The counterfactual markup component is

$$PD^{cf} = \frac{1}{T}\sum_{t=1}^{T}\left[\overline{(p^{cf}-mc)}_{ot}^{cf} - \overline{(p^{cf}-mc)}_{not}^{cf}\right]. \tag{23}$$

Comparing PD^{cf} with the baseline markup component indicates whether income heterogeneity is an important source of differential markups between organic and non-organic products.

4 Estimation

4.1 Estimation Details

The key issue in the demand model is to estimate equation (6). This is a system of J_t equations and J_t unknowns. where J_t is the number of products in each market. The insight of Berry et al. (1995) is to perform a non-linear change of variables, i.e. $\delta_t \equiv D_t^{-1}(S_t, \theta_2)$, where S_t is the vector of observed market shares.

I use simulations to solve equation (6). In practice this equation becomes:

$$s_{jt} = \frac{1}{I_t}\sum_{i=1}^{I_t}\frac{exp\{\delta_{jt}+\mu_{ijt}\}}{\sum_{k=0}^{J_t} exp\{\delta_{kt}+\mu_{ikt}\}}, \tag{24}$$

where I_t is the number of simulations, and $\mu_{ijt} = [p_{jt}, x_{jt}]' * (\Pi D_i + \Sigma \nu_i)$, D_i is the i-th draw of the observed consumers characteristics from the CPS, at market t, and ν_{it} is the i-th random draw of the unobserved consumer characteristics variables, ν_i.

In order to perform this simulation, I assume that D_i and and ν_i are independent and I use Halton sequences to simulate the integral.

There are other issues that must be resolved to perform the estimation and I follow the best practices suggested by Conlon and Gortmaker (2020).

First, matrix Σ is restricted to be diagonal, which means that the unobserved consumer preference for different product characteristics are independent of one another.

D_i is specified to include only one variable: income. I use only this demographic characteristic because it does not capture only heterogeneity in purchase power, but also other characteristics. It is likely that richer households are also more educated, and therefore, have more information and/or are environmental concerned.

Regarding the observed products' characteristics, I use the following variables: price, Display, and Feature. I also add quarter and MSA dummies.

Finally, I do not estimate all parameters in the coefficient matrix for product and household characteristics interaction, Π. Specifically, Feature and Display, like the advertisement variable in Nevo (2000), do not present a random coefficient and are not interacted with the households' characteristic.

However, there are still non-observable characteristics of products that do not vary per market. Also, ξ_j in equation (2) is not observed in the data. Therefore, I include a set of product dummies to replace $x_j \beta + \xi_j$ in the following way:

$$Product_j = x_j \beta + \xi_j. \tag{25}$$

This strategy is similar to the minimum-distance procedure used by Nevo (2000).

In order to retrieve the taste coefficients, β, I regress the estimated product effects, from the GMM estimation, on the observable characteristics.

4.2 Identification

I estimate the parameters of the demand system presented in Section 3 by exploiting a population moment condition and a structural error term to form a non-linear GMM estimator. Let $Z = [z_1, \ldots, z_M]$ be a set of instruments such that $E[Z'\dot{\phi}(\theta^*)] = 0$, where θ, a function of the model parameters, is an error term defined below and θ^* denotes the true value of these parameters. The GMM estimate is

$$\hat{\theta} = \arg\min_{\theta} \phi(\theta) Z A^{-1} Z' \phi(\theta), \tag{26}$$

where A is a consistent estimate of $E[Z'\phi\phi' Z]$.

4.3 Instruments

I need a set of exogenous instrumental variables to properly estimate the demand system. Since I have different products in different markets, I follow the literature (e.g. Berry et al. 1995; Bresnahan et al. 1997; Sudhir 2001; Petrin 2002) and use the well known BLP instruments. This set of instrumental variables contains variables capturing the average product characteristics of the UPCs in the same market, and the number of products, by firm ownership and product category, in the same market. The main idea behind this type of instrument is that firms make pricing decisions based on the number of competing products they face in each market, and how similar these products are to theirs.

Another set of instruments is constructed following Hausman (1994) and Nevo (2001). It is the average price of the same UPC in other markets. These are correlated to the price variable, but not to the error term under the assumption that the unobserved UPC-market specific demand shifting factors are independent across markets. If this assumption does not hold then this instrument is not valid. For instance, national advertising campaigns can shift demand in different markets at the same time. To lessen this concern, I control for advertising at the UPC-market level.

Whether or not a good faces close substitutes is an important determinant of its demand. Thus, a third set of instruments is based on how similar a product is to its competitors. These instruments were proposed by Gandhi and Houde (2019) and they are based on exogenous measures of product differentiation. These instruments exploit products' relative isolation in the characteristic space and they perform well to identify heterogeneous consumer preferences.

As a last set of instruments, I also follow Nevo (2001) and use supply shifters. I use regional dummies and population density to control for the land cost of retailing, and also hourly wage in the supermarket sector to control for the labour cost of retailing. Since these are supply shifters, they are not likely to be correlated with demand shifters.

Finally, I use optimal instruments, as proposed by Reynaert and Verboven (2014). They showed that the use of Chamberlain (1987) optimal instruments increases the estimator's efficiency and stability in a BLP framework, especially allowing for a more precise estimation of the standard deviations of the random coefficients.

5 Results

Table 4 presents the demand estimates. The first column reports estimates from a simple OLS logit model, while the second column reports estimates from the IV logit model. Column 3 reports the mean taste parameters from the BLP estimation, and columns 4 and 5 report, respectively, the estimated standard deviations of the random coefficients and their interactions with household income.

The OLS and IV logit estimates have the same qualitative signs as the BLP estimates. I therefore focus on the random-coefficient specification. The price coefficient is negative and statistically significant, as expected. The coefficients on the advertising variables are positive, suggesting that feature and display activity increase demand, although only the coefficient on display is statistically different from zero.

The preferred specification allows for random coefficients on the intercept, price, and the organic indicator, and also allows the price and organic coefficients to vary with household income. The estimated standard deviation of the random price coefficient is zero, at the lower bound of the parameter space. This restriction is not imposed ex ante; rather, the data do not indicate residual unobserved heterogeneity in price sensitivity once observed income heterogeneity is included. Accordingly, the table reports the estimate but does not report a conventional standard error for this boundary parameter. This is in line with Nevo (2001), who estimates this parameter and finds that it is not statistically different from zero.

Importantly, this does not imply homogeneous price sensitivity. The interaction between price and income is economically large and precisely estimated, indicating that price sensitivity varies systematically with household income. The boundary estimate therefore suggests that the relevant heterogeneity in price sensitivity is captured by observed income rather than by an additional unobserved random price component. As a robustness check, I also estimate specifications in which the random price coefficient is fixed at zero and in which alternative restrictions are imposed on the organic-income interaction. The main results are qualitatively unchanged across these specifications.

The signs of the organic coefficients correspond to distinct components of preferences. The mean coefficient on organic is negative, which is consistent with the low average market shares of organic products relative to regular products after controlling for prices, promotions, product fixed effects, MSA fixed effects, and quarter fixed effects. The estimated standard deviation of the organic random coefficient is positive, but it is not statistically different from zero. Additionally, the organic-income interaction is negative. Thus, the evidence does not support the view that higher-income households have systematically higher direct utility from the organic attribute. I return to this result in the counterfactual exercise in Section 6.1.

Using the estimated utility parameters, I compute the own-price elasticity for each UPC. The left panel of Figure 1 reports the mean of these elasticities across markets. The estimates are in line with those reported by Nevo (2001) and Michel and

Table 4. Demand Estimates

Variable	OLS	IV	BLP Mean	BLP SD	BLP Income
Price	-17.670***	-18.485***	-33.615***	0.000	4.460***
	(0.107)	(0.116)	(10.156)		(1.205)
Feature	1.272***	1.256***	0.065		
	(0.014)	(0.014)	(0.100)		
Display	1.263***	1.251***	0.581***		
	(0.029)	(0.029)	(0.117)		
Organic			-0.629^{a}***	1.371	-0.915***
			(0.145)	(0.889)	(0.227)
Low Sugar			0.616^{a}***		
			(0.230)		
Size (oz.)			-0.038^{a}***		
			(0.012)		
Constant			-8.296***	4.738***	
			(0.206)	(0.765)	
Observations	138,165	138,165	138,165		
Markets	480	480	480		
MSA and quarter FE	Yes	Yes	Yes		

Note: * denotes significance at 10%, ** at 5%, and *** at 1%. OLS and IV columns report simple logit estimates. The IV column instruments price with the demand instruments. "a" denotes estimates from the minimum distance procedure using the estimated UPC dummy coefficients from the GMM estimation.

Weiergraeber (2018), and indicate that consumers are sensitive to price changes at the product level.[19] Organic cereals have more elastic own-price demand than non-organic cereals, which is consistent with their higher prices and smaller market shares.

The right panel in Figure 1 reports aggregate demand elasticities by market. These elasticities capture the response of total category sales to a proportional price change, such as a sales tax applied to all products in a category. In contrast to the product-level elasticities, aggregate demand for non-organic cereal is close to unit elastic, reflecting the importance of ready-to-eat cereal in household consumption and the limited substitution to the outside good. Aggregate demand for organic cereal is substantially more elastic, suggesting that consumers are more willing to reduce purchases of organic cereal when prices increase.

[19] Michel and Weiergraeber (2018) estimate a nested logit model.

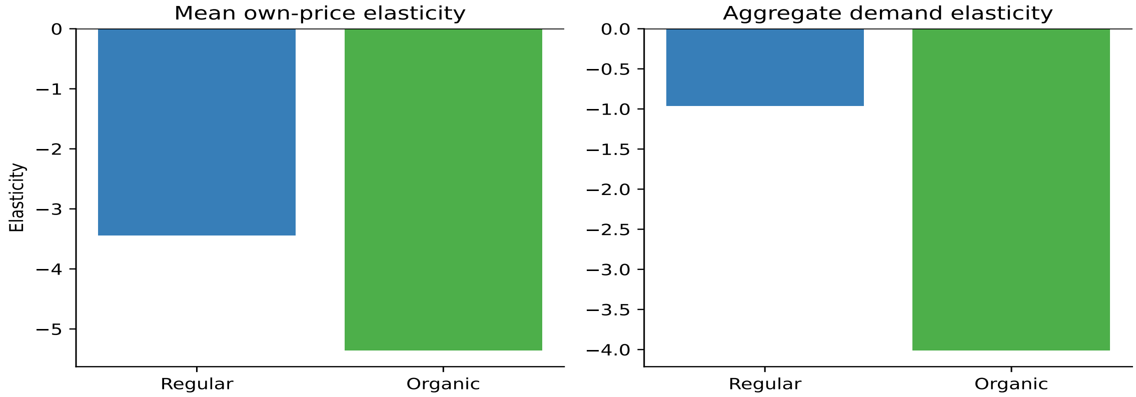

Figure 1. Price elasticities

I use the estimated demand elasticities and the supply-side first-order conditions to recover marginal costs and margins for each UPC in each market. These results are summarised in Table 5.[20] The average marginal cost is higher for organic products than for regular products, which is consistent with the idea that the organic price premium partly reflects higher production costs.

The margin results tell a different story. Regular cereals have, on average, higher margins than organic cereals. Thus, although organic products are more expensive and have higher marginal costs, they do not appear to carry higher absolute markups. This already suggests that the organic price premium is unlikely to be driven by firms charging higher margins on organic products.

To give an idea of the margin distribution, I plot its distribution, for both varieties, in Figure 2. It is clear that that the majority of organic products have a markup lower than the majority of non-organic products.

Table 5. Recovered Marginal Costs and Margins

Statistic	Organic MC	Regular MC	Organic Margin (%)	Regular Margin (%)
Mean	0.120	0.070	22.416	38.686
Standard deviation	0.041	0.041	8.017	13.293
Maximum	0.315	0.354	70.680	99.967
Minimum	0.011	0.000	9.198	9.248

Note: The table excludes observations with negative recovered marginal costs. Marginal costs are measured in dollars per ounce. Margins are 100 times markup divided by price.

[20] A total of 174 out of 138,165 product-market observations have negative marginal costs (0.13%). I exclude these observations from Table 5 and from the subsequent counterfactual exercises.

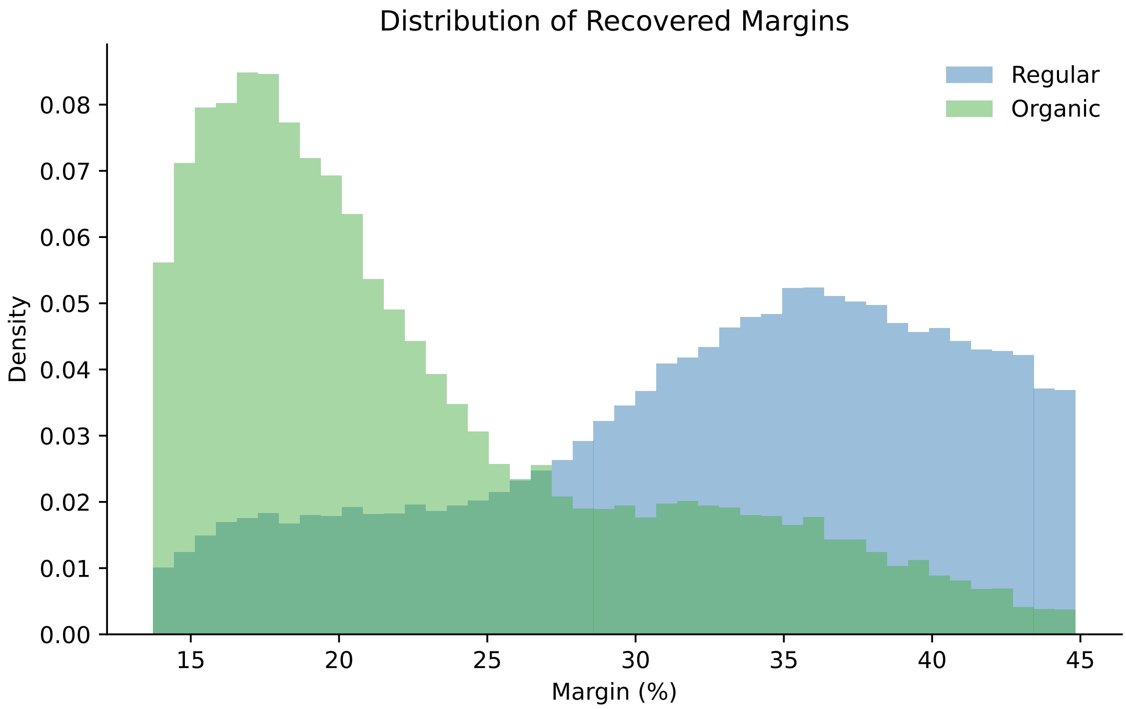

Figure 2. Margin distribution

Following the decomposition procedure described in Section 3.3, I decompose the organic price premium into a marginal-cost component and a markup component. The results are presented in Table 6. All entries are organic minus non-organic differences, measured in dollars per ounce, and computed within markets using share-weighted averages. The first column reports the organic price premium, the second column reports the difference in marginal costs, and the third column reports the difference in markups. The final column reports the share of the organic price premium accounted for by the markup component.

The baseline decomposition shows that organic products are, on average, 3.1 cents per ounce more expensive than regular products. However, the marginal cost difference is larger, equal to 3.6 cents per ounce. As a result, the markup difference is negative, around -0.5 cents per ounce. This markup difference is small in absolute value, but it is economically informative because it has the opposite sign of the price-discrimination hypothesis. Thus, the organic price premium is more than fully explained by higher marginal costs, and organic products do not carry higher markups than regular products.

The remaining rows provide robustness checks. The matched-product comparison compares organic products to similar regular products, focusing on products from the same firm and with similar characteristics. In this case, the price difference is very small, but the markup difference remains negative. The within-firm-market comparison restricts attention to comparisons within the same firm and market, and again shows that the cost gap is larger than the price gap. Finally, the IV logit row repeats the supply-side recovery using the simpler IV logit demand estimates. This alternative model also produces a small negative markup gap. Across all rows, the decomposition exercise suggests that the organic premium is explained by higher marginal costs rather than by higher markups.

Table 6. Decomposition of the Organic Price Premium

Sample	Price gap	Cost gap	Markup gap	Markup share
Baseline	0.031	0.036	-0.005	-0.144
Matched, same firm	0.001	0.005	-0.003	-2.188
Within firm-market	0.020	0.023	-0.003	-0.173
IV logit	0.031	0.032	-0.001	-0.017

Note: Gaps are share-weighted organic minus regular differences. The baseline sample excludes negative recovered marginal costs. Markup share is the markup gap divided by the price gap.

To analyse whether this result is driven by any specific MSA, in Figure 3 I present the result of this decomposition for each MSA. The negative pattern happens in 29 out of the 30 locations, and in the only one that it is positive the absolute value is small. Therefore, the result is not driven by any specific location and the pattern is observed in all the country.

6 Counterfactual and Robustness

6.1 Income-distribution counterfactuals

Table 7 reports the income-distribution counterfactuals. The first row reproduces the observed baseline decomposition, after excluding products with negative marginal costs. The second row reports the model baseline, obtained by resolving equilibrium prices using the estimated demand system, the observed income draws, and the

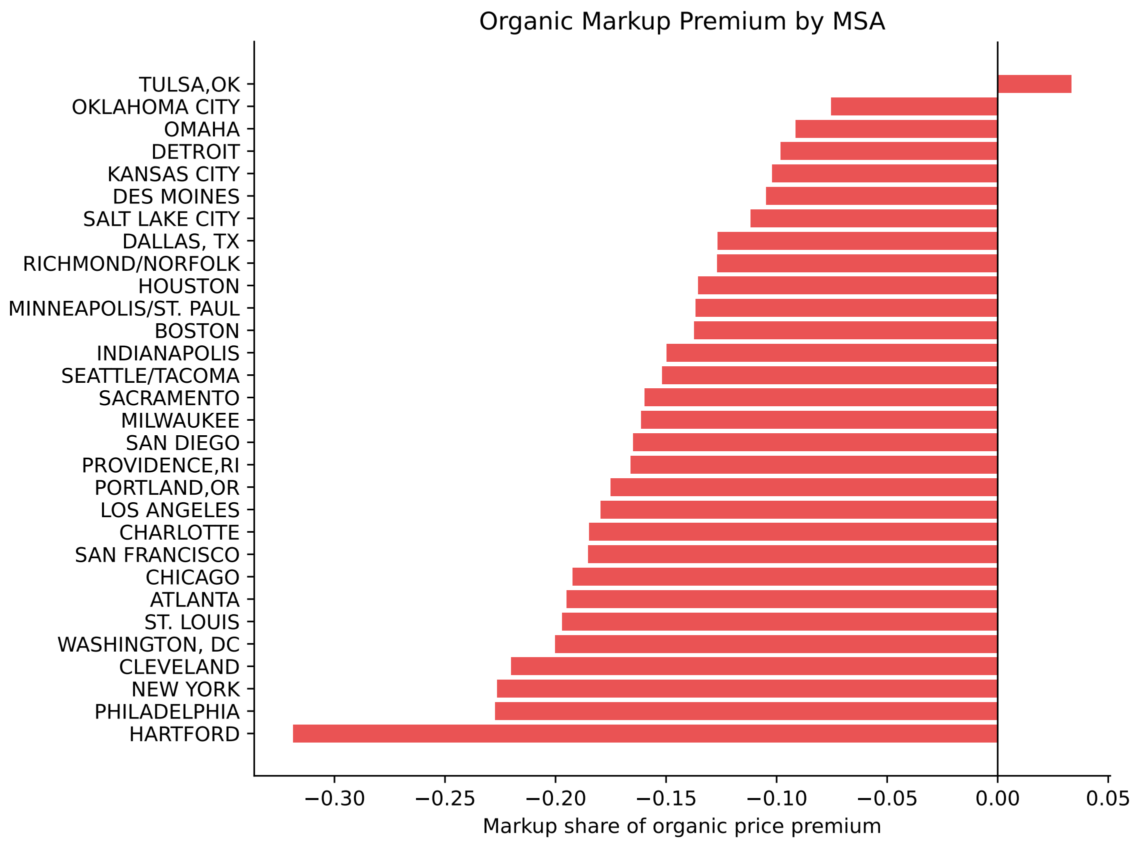

Figure 3. Decomposition by MSA

marginal costs. The close match between the observed baseline and the model baseline shows that the counterfactual procedure accurately reproduces the observed pricing equilibrium.

The final two rows modify the income distribution used in the consumer draws. In the within-market counterfactual, all households in an MSA-quarter are assigned the same log income. In the national counterfactual, all households are assigned the same log income across all markets. In both cases, product qualities and marginal costs are held fixed, and equilibrium prices are recomputed. If the organic premium were driven by firms charging higher markups in markets with richer organic consumers, removing income heterogeneity should substantially reduce the organic markup premium.

The results do not support this mechanism. Equalising income increases the organic price gap slightly, and the share-weighted cost gap also changes slightly because equilibrium shares change. However, the underlying marginal costs are held fixed.

The markup gap remains negative and small. The markup share of the organic price premium rises from around -14% in the baseline to around -5%, but it does not become positive. Thus, income heterogeneity is not the source of higher organic prices. The counterfactual confirms that the organic premium is explained by costs rather than by firms extracting higher markups from high-income consumers.

Table 7. Income Heterogeneity Counterfactual

Scenario	Price gap	Cost gap	Markup gap	Markup share
Observed baseline	0.031	0.036	-0.005	-0.144
Model baseline	0.031	0.036	-0.005	-0.144
Equal income within MSA-quarter	0.037	0.039	-0.002	-0.050
Equal income nationally	0.037	0.039	-0.002	-0.050

Note: Counterfactuals exclude products with negative recovered marginal costs, hold product qualities and marginal costs fixed, and resolve Bertrand-Nash prices after changing the income distribution in the consumer draws.

6.2 Organic-attribute counterfactual

Table 8 reports the counterfactual with the measure described in Section 3.4. The results again provide no evidence of positive price discrimination against organic consumers. The baseline markup difference, PD_{All}, is negative, i.e. organic products have lower markups than regular products. After removing the organic attribute and adjusting marginal costs, the restricted markup difference remains negative. The implied organic-specific component, *PD*, is also negative. Thus, even under this alternative counterfactual definition, the organic attribute does not generate higher markups. This reinforces the main decomposition result that the organic price premium is driven by higher marginal costs rather than by price discrimination.

7 Conclusion

In this paper, I study the organic price premium in the ready-to-eat cereal market. Organic products are more expensive than regular products, but this price difference can reflect either higher production costs or higher markups. To separate these mechanisms, I estimate a random coefficient discrete choice demand model, recover product-level marginal costs and markups using the implied demand elasticities and

Table 8. Price Discrimination with Respect to the Organic Attribute

Average Price Difference ($)	0.0314
PD_{All} ($)	-0.0045
$PD_{Restricted}$ ($)	-0.0019
PD ($)	-0.0026

Note: Values are in dollars per ounce. The table reports the share-weighted measure, using product shares within organic status and market. Products with nonpositive baseline or counterfactual marginal costs were not included in the experiment.

a supply-side pricing model, and decompose the organic price premium into cost and markup components.

The main result is that the organic price premium is explained by higher marginal costs rather than by higher markups. Organic cereals are, on average, more expensive than regular cereals, but the marginal cost difference is larger than the observed price difference. As a result, the organic markup gap is negative. This finding is robust to alternative comparisons, including matched products, within-firm-market comparisons, and a simpler IV logit demand model.

I also conduct two counterfactual exercises. First, I change the income distribution in the consumer draws and resolve equilibrium prices. If firms charged higher organic markups because organic consumers are richer or less price sensitive, removing income heterogeneity should reduce the organic markup premium. The results do not support this as the markup gap remains negative and small. Second, I remove the organic attribute from originally organic products, adjust their marginal costs by the estimated organic cost component, and solve again for equilibrium prices. This exercise also provides no evidence that the organic attribute itself generates higher markups.

These findings suggest that, in this market, the organic premium should be understood primarily as a cost premium rather than as evidence of price discrimination. Hence, it shows that the higher prices observed for organic cereals are not driven by firms extracting higher margins from consumers with stronger willingness to pay for organic products.

The results of this paper are subject to some caveats. First, no product-level cost data are available to evaluate the accuracy of the marginal costs directly. Second, the analysis assumes a passive role of grocery stores in the pricing decision. This implicitly assumes that retailers' costs and margins are constant. Although this is a commonly used assumption, it could be the case that the bargaining power is on the part of retailers, and not the manufacturers (Villas-Boas 2007, 2009; Bonnet and Dubois 2010). Analysing this issue would require richer data on the supply side and is a potential avenue for future research.

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