Spatial Differences in Premiums for High Quality Products: A Case Study of Organic Food*

Seung-Hyun Hong
Department of Economics
University of Illinois, Urbana-Champaign

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Abstract

This paper investigates the roles of markups and costs in explaining the higher prices of high-quality products and explores why price premiums for these products are lower in wealthier or more educated areas. Using scanner data on baby food prices and quantities, I document that organic products generally command substantial price premiums over non-organic alternatives, but these premiums decline with county-level income, population, and education. By estimating a random coefficient nested logit demand model and assuming Bertrand-Nash pricing, I recover product-specific markups and costs across local markets. I find that organic products typically have higher costs but lower markups compared to non-organic products. For both products, markups increase and costs decrease with county-level income and education. For organic products, however, the increase in markups is less pronounced, while the decrease in costs is more pronounced, aligning with the observed spatial variation in premiums. Counterfactual analysis reveals that removing competition among organic products reduces spatial differences in organic premiums by about half, mainly due to increased markups in richer or more educated areas. Spatial differences in costs, likely tied to distribution rather than production, explain the remaining price variations. Additionally, wealthier or more educated areas benefit more from organic products due to higher consumer surplus and variable profits. These findings underscore the role of local market structures on spatial variations in price premiums, consumer welfare, and market efficiency.

Keywords: Organic Product; Price Premium; Spatial Pricing; Local Market Structure; Preference Externality

JEL classification: D12, L1, L66, R22, R32

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1 Introduction

New products are often introduced as superior alternatives to existing ones, claiming higher quality and commanding premium prices. A prominent example is organic products.[1] In recent years, many new organic brands have entered the market, typically priced higher than their non-organic counterparts. This trend can be concerning, if firms exploit consumers' perceptions of quality by charging inflated markups. This is likely under monopoly non-linear pricing (Mussa and Rosen, 1978), in which a monopolist offers varying quality levels to induce consumer self-selection and extracts higher markups from those willing to pay more for quality.[2] In particular, markups may be even higher in markets with more consumers willing to pay a premium, resulting in greater price premiums for organic products.

However, Figure 1 reveals a puzzling trend: although organic baby food is generally more expensive than its non-organic alternatives, the price premiums tend to be lower in high-income counties, where one might expect a greater willingness to pay for quality. This raises two key questions. First, are organic products more expensive due to inflated markups or genuinely higher costs associated with better quality? Second, why are price premiums for organic products lower in high-income areas compared to low-income areas?

A simple explanation for these questions might attribute the observed pattern to the unique characteristics of baby food markets. However, recent studies on inflation inequality suggest that this pattern, particularly regarding spatial variations in premiums, reflects a broader trend. For instance, Jaravel (2019) finds that inflation rates decline with income, while Handbury (2021) shows that the high-income consumption bundle is relatively cheaper than the low-income one in wealthier cities. Given that organic products are often favored by higher-income consumers, this broad trend is also consistent with the pattern shown in Figure 1, suggesting that the simple explanation above is inadequate.

[1] Organic foods in general are not exactly new products, given that traditional farming practiced for thousands of years was in fact organic. During the 20th century, however, food production was mostly not organic, and non-organic foods became dominant. In this context, organic products have been reintroduced, and various new organic products have been launched in recent years.

[2] Most markets are characterized as oligopoly rather than monopoly, but quality-based price discrimination under oligopoly may not be the same as monopoly price discrimination (Stole, 2007). Nevertheless, Verboven (2002) provides significant evidence for quality discrimination of a monopolistic type in European car markets where multiple firms compete with each other. In particular, he finds that a sizable share of the price premium for a diesel car relative to a gasoline car is attributed to higher markups from price discrimination.

The literature on inflation inequality offers potential explanations for this pattern. Jaravel (2019) provides evidence that increasing relative demand for high-income consumers' products leads to greater product variety and lower inflation for these goods. Handbury (2021) provides evidence suggesting that local distributors cater to local tastes, generating "preference externalities" (Waldfogel, 2003) driven by variations in the local mix of retail chains. These factors may partly explain the trends observed in Figure 1. Nevertheless, other explanations are also possible. For example, consumers in wealthier or more educated areas might be more informed about the true quality of organic products,[3] while those in other areas who purchase organic products might overvalue their quality, in which case spatial variations in price premiums may reflect the extent to which consumers in each area are informed about product quality.

More importantly, these potential explanations do not fully address why high-quality or organic products are more expensive and how much of these price differences can be attributed to markups versus marginal costs. Furthermore, the extent to which spatial variations in price premiums arise from differences in markups or costs remains unclear. Distinguishing between markups and costs is crucial because the policy implications may differ significantly. For example, if spatial differences in price premiums are primarily driven by spatial variations in markups, rather than production costs or transportation costs, antitrust interventions may be necessary in markets where markups are excessively high.

Therefore, this paper investigates the roles of markups and costs in explaining the higher prices of high-quality products and explores their roles behind spatial variations in price premiums for these products. To this end, I use the NielsenIQ Retail Measurement Services (RMS) scanner data on prices and quantities for baby food markets. I consider the baby food industry because many new premium organic products have been introduced in this industry, and the key pattern shown in Figure 1 is similar to those from the literature on inflation inequality. Moreover, it is plausible that more consumers (i.e., parents of babies) may be willing to pay more for organic baby food, so that this industry might be one of industries where organic products are expected to have inflated markups.

[3] Bronnenberg et al. (2015) show that more informed consumers are less likely to pay extra to buy national brands, and a sizable share of the brand premium for health products can be explained by misinformation.

Using the RMS data, I first document that organic products generally command substantial price premiums over non-organic alternatives, but these premiums decline with county-level income, population, and education. The data also reveal that organic products have smaller market shares in low-income or less educated counties, but larger market shares in high-income or more educated counties. Similar patterns are observed in terms of revenues and product variety as well. These patterns are consistent with preference externalities, in that wealthier or more educated areas are likely to include more consumers who prefer organic products, which attracts more organic firms and products in these markets. However, this does not tell us whether these markets have lower markups for organic products, or experience any welfare improvement from an increase in consumer or producer surplus.

To investigate the roles of markups and costs behind spatial variations in organic premiums and further examine welfare consequences, I use the data on local market shares and prices, and estimate a random coefficient logit demand model (e.g., Berry, et al, 1995; Nevo, 2001; Miller and Weinberg, 2017). I follow the standard approach, but one difference is that I use exogenous variations from product recalls: first, as temporary supply shifters, and second, as proxies for quality signal.[4] Assuming Bertrand-Nash pricing, I recover markups and marginal costs for products sold in each local market. I find that organic products typically have higher marginal costs but lower markups compared to non-organic products. Moreover, markups tend to increase and costs tend to decrease with county-level income and education. For organic products, however, the increase in markups is less pronounced, while the decrease in costs is more pronounced compared to non-organic products, which explains the observed spatial variations in organic price premiums.

Counterfactual analysis reveals that eliminating competition among organic products alone reduces spatial differences in organic premiums by about half. This reduction is primarily driven by an increase in markups for organic products in wealthier or more educated areas. In contrast, competition between organic and non-organic products does not significantly affect spatial variations in organic premiums. The analysis also suggests that spatial differences in costs – likely reflecting distribution costs such as transportation or warehousing

[4] Recalls are reasonably exogenous. They also provide information on true (negative) quality, which could influence consumers' perceptions about product quality. Hence, recalls could be used to control for potential spatial variations in price premiums related to consumers' knowledge. See Section 2.1 for more details on recalls considered in this paper.

rather than production – account for the remaining spatial variations in organic price premiums. Furthermore, wealthier or more educated areas derive greater benefits from organic products, not only through higher consumer surplus but also due to higher variable profits compared to poorer or less educated areas. However, I do not find any significant evidence for the role of consumer information captured by recalls in spatial variations of price premiums. These findings emphasize the critical roles of local market structures and cost structures in shaping spatial variations in price premiums, consumer welfare, and market efficiency.

This paper relates to several strands of literature. First, this paper is related to studies on inflation inequality discussed above (Jaravel, 2019; Handbury, 2021) and reviewed in Jaravel (2021). Unlike this literature, however, this paper considers an individual industry and a specific type of high quality products, which enables me to use a standard tool in industrial organization to recover markups and costs across geographic markets. Second, the literature on preference externalities (e.g., Waldfogel, 2003; George and Waldfogel, 2003) is related to this paper, given that preference externalities explain why wealthier or more educated areas have stronger demand for organic products and more organic firms and products. This paper extends the literature by examining spatial variations in price premiums, markups, costs, as well as consumer and producer surplus. Third, this paper is related to the literature on recalls.[5] Though recalls are not the main focus of this paper, I use their exogenous variations to help identification. Lastly, this paper builds on the large literature in industrial organization that has estimated markups and costs in various industries (Berry, et al., 1995; Verboven, 1996; Nevo, 2001). However, most studies focus on national markets and variations over time. By shifting the focus to spatial variations, I uncover how markups and costs vary across local income and education levels, particularly in the context of organic versus non-organic products.

The rest of the paper is organized as follows. Section 2 describes the data and provides descriptive patterns in the data. The empirical model is outlined in Section 3. Section 4 reports the model estimates and the distribution of costs and markups. This section also presents the results from the counterfactual analysis. Section 5 concludes the paper.

[5]A large number of papers in this literature (e.g., Jarrell and Peltzman, 1985) examine the stock market response to recalls and measure the effect of recalls on firm values. Some papers examine the effects on sales to investigate the role of reputation, particularly focusing on spillover effects or "collective reputation" (e.g. Freeman, et al., 2012; Bai, et al., 2022).

2 Data

The primary source of my data is the NielsenIQ Retail Measurement Services (RMS) scanner data. The RMS data provides information on prices, quantities, and characteristics of products, as well as information on store characteristics. I additionally use the American Community Survey (ACS) data for county-level demographic information. In what follows, I briefly describe the baby food industry, and then provide details on the datasets. Lastly, this section presents descriptive patterns from these datasets.

2.1 Industry Background

This paper examines the strained baby food module, where modules refer to product categories in the RMS data that consist of numerous Universal Product Codes (UPCs) for the same type of products. The strained baby food module includes pureed or strained baby food typically contained in a jar or a pouch. This industry has one dominant firm – Gerber – and several medium-sized firms, as well as many small firms. During the period from 2011 to 2016, Gerber accounts for about 53% of sales in this module. During the same period, BeechNut is the next (11.5%), followed by Plum Organics (9.5%), Earth's Best (6.5%), and Stonyfield (6%) in terms of their sales. All other firms have much smaller sales. The majority of Gerber's products are non-organic, but it also offers organic products. Several firms such as Plum and Earth's Best offer only organic products.

Though a squeezable pouch is ubiquitous for baby food products these days, it did not exist until it was first introduced by Plum Organics. This firm was founded in 2007 and specializes in selling premium organic baby foods. Plum Organics is also the first firm to package pureed fruits and vegetables in squeezable pouches that even babies can use by themselves. This innovative packaging was successful, and this firm quickly became a leading provider for premium organic baby foods.[6] However, this packaging was not patented, and most other firms started to use pouches for their baby food products.[7] This change in

[6] Plums' success led to the acquisition by Campbell Soup Company. According to the annual report from Campbell, it acquired Plum (formerly Plum Inc.) at $249 million in June 2013. However, Campbell completed the sale of Plum for $101 million in 2021, and Plum was sold to Sun-Maid Growers of California.

[7] According to the annual report from Nestle (Gerber's parent company), Gerber introduced its first pouch products in 2012.

packaging and the growth in the organic segment characterize this industry in the 2010s.

I focus on the baby food industry for the following reasons. First, similar to other industries with new premium organic products, the baby food industry has also witnessed a surge in new organic products that are typically high-priced and advertised as premium brands. Second, as shown in Figure 1, the key pattern in this industry is similar to those from the literature on inflation inequality. Third, while many product modules in the RMS data include only a small fraction of organic products, the baby food product module is one of exceptions with a higher fraction of organic products. Fourth, it is plausible that more consumers, that is, parents of babies, may be willing to pay more for organic baby food, which suggests that inflated markups for organic products are expected in this industry. Fifth, by studying a specific industry, I can use standard tools in Industrial Organization to recover markups and costs.

One interesting event in this industry is a series of recalls by Plum Organics. Some firms (e.g., Gerber, Earth's Best) also experienced recalls, but the scale of their recalls is small.[8] In contrast, Plum experienced a series of recalls during my sample period: August 2013, November 2013, and October 2014. Each recall involves different UPCs from other recalls by Plum. All three recalls had Class II classification.[9] The recalls in August 2013 and October 2014 had much smaller scale than the recall in November 2013. The recall in November 2013 involved recalling about 600,000 units and was terminated after 16 months. While the recall in October 2014 was related to potential choking hazard, the recalls in August 2013 and November 2013 were related to potential defects in packaging. The effect of recalls is not the main focus of this paper. Nevertheless, my empirical model described in Section 3 incorporates Plum's recalls, because recalls are reasonably exogenous, and they could potentially help identification by providing temporary supply shifters as well as proxies for negative quality signal that is typically unobserved in the absence of recalls.

[8] The recall information is obtained from the FDA Data Dashboard which provides the details on recalls, including UPCs of recalled products if available. However, many records in the FDA data do not include UPCs. Even if UPCs are available, they need to be searched through the text in a separate URL, and they have different formats that cannot be directly matched with UPCs in the RMS data. For this reason, I manually searched the FDA data to look for several major firms in the strained baby food module.

[9] According to the FDA definition, Class II classification is issued in "a situation in which use of a violative product may cause temporary or medically reversible adverse health consequences or where the probability of serious adverse health consequences is remote."

2.2 Data Description

The RMS data include weekly store-UPC-level price and quantity data in various modules for over 40,000 stores (groceries or mass merchandisers). I use the RMS data for the strained baby food module from 2011 to 2016. The RMS data do not have any data for this module in 2009, and all sales information is missing in 2010. As a result, I use the data from 2011. The main analysis uses county-level quarterly data. The RMS data provide the county name and the three-digit zip code where a store is located. Yearly demographic information is publicly available at the county level from the ACS data, but not at the three-digit zip code level. In addition, weekly or monthly sales even at the county level are often small or missing for many products. For this reason, I aggregate the data by county, quarter, and product.

In this paper, products are major brands based on "brand description" in the RMS data. I focus on 8 major brands whose brand name is essentially the same as its firm name.[10] A firm can have at most two products in my analysis, but during my sample period, most firms specialize in either organic products or non-organic products. Hence, most firms have only one product in my analysis.[11] One exception is Gerber that offers both organic (Gerber Organic) and non-organic (Gerber). The other exception is Plum Organics, for which I separate recalled UPCs from other UPCs that were never recalled. A product's quantity is the number of servings that is equal to the product's volume (in each county and quarter) divided by the modal size. A product's price is the quantity-weighted average price. Note that all dollar values in this paper are deflated by using CPI. More details on these variables and other key variables are given in Appendix.

2.3 Descriptive Patterns

In this section, I document key patterns from my data. I begin by exploring spatial variations in prices, and then examine spatial variations in other key variables. Figures 2-4 plot the

[10] These include Gerber, Gerber Organic, Plum Organics, BeechNut, Earth's Best, Happy Baby, Stonyfield, and Ella's Kitchen. These brands account for about 90% of total sales during my sample period. For all other brands, if its brand name includes one of these major brand names, I include them in those products. Otherwise, I put them into "other organic" product or "other non-organic" product. These other products account for only about 5% of total sales.

[11] Though a majority of BeechNut's products are non-organic, it still has a small number of organic products. Due to their small market shares, these organic products are dropped.

county-quarter level quantity-weighted average prices for organic products vs. non-organic products across different counties in terms of population, income, and education. Each blue triangle (or red circle) represents the average price of organic (or non-organic) products in each county-quarter. The blue (or red) line is the fitted line for organic (or non-organic) prices. The gradients of these fitted lines are reported in Table 1, where the gradient for organic (or non-organic) prices is presented in column 1 (or column 2). The county-quarter level price premium – the difference between organic prices and non-organic prices – is also fitted, and its gradient is reported in column 3.

All these figures show that organic products are generally more expensive than non-organic products, which is not surprising. In contrast, spatial variations in price premiums are more surprising. With respect to county population, Figure 2 shows that as county-level total population (in the top figure) or population aged between 0 and 9 (in the bottom figure) increases, organic prices tend to decrease, whereas non-organic prices decline only slightly. Hence, the price premium decreases with county-level population. The magnitude of this decline is moderate, since column 3 in Panels A and B of Table 1 indicate that if county-level population is 10% larger, the price premium is lower by only about \$0.003. Due to this small magnitude, the rest of the paper does not focus on spatial variations in terms of population, although their patterns are consistent with the patterns in other dimensions.

In terms of income, Figure 3 reveals that organic prices decrease with the log of county-level median household income, while non-organic prices do not change much regardless of county-level income. As a result, the price premium declines with county-level income as well. Panel C of Table 1 implies that if a county has a 10% higher income than another county, its price premium for baby food is lower by \$0.014, compared to the other county. With respect to education, Figure 4 shows that organic prices tend to be lower in counties with more college graduates, whereas non-organic prices tend to be only slightly lower in those counties. Panel D of Table 1 indicates that if a county has more college graduates than another county by 10 percentage points, it has a lower price premium than the other county by \$0.049.

These patterns are puzzling, because wealthier or more educated areas are likely to have more consumers with higher willingness to pay for organic products. To examine potential sources behind spatial differences in price premiums, I further consider spatial variations in other variables. Figure 5 considers the market share of organic (or non-organic) products among inside goods. This figure is similar to Figure 4, except that the y-axis is now the market share, instead of the price. The figure shows that organic products have much smaller market shares in counties with fewer college graduates than in counties with more college graduates, which suggests that organic products are likely to have higher demand and supply in areas with more college graduates, compared to non-organic products. Figure 6 shows a similar pattern in terms of the number of products measured by UPCs (in the top figure) and flavors (in the bottom figure). The number of organic products is larger in counties with more college graduates.

In Figure 7, I consider county-level quarterly revenues. The bottom figure plots the relationship between the fraction of college graduates and the revenue of all baby food products. It reveals that counties with more college graduates tend to generate higher revenues, likely reflecting higher demands in these areas that can accommodate more firms and products in general. This suggests that these areas may also have lower market concentration in this industry. In fact, Figure 8 shows that the Herfindahl-Hirschman Index (HHI) is indeed lower in counties with more college graduates.

The top figure in Figure 7 plots the relationship between the fraction of college graduates and the revenue for organic vs. non-organic products, which shows that counties with fewer college graduates tend to generate lower revenues from organic products, compared to non-organic products. This suggests that less educated areas may be able to accommodate only a small number of organic firms and products, so that local markets in these areas may be less competitive. Figure 9 shows that counties with higher market concentration tend to have higher prices particularly for organic products.

These patterns are consistent with preference externalities (Waldfogel, 2003), in that wealthier or more educated areas are likely to include more consumers who prefer organic products, which attracts more organic firms and products in these markets. However, more organic firms and products in these areas also coincide with higher demand for organic products, and the resulting equilibrium prices for organic products are not necessarily lower in these areas. Therefore, preference externalities alone do not necessarily imply that price premiums for organic products should be lower in wealthier or more educated areas.

Moreover, price premiums can be associated with the extent to which consumers are informed about the true quality of products. Hence, spatial variations in price premiums may also reflect the spatial distribution of informed consumers. For example, it may be possible that although most consumers in less affluent or less educated areas might not prefer organic products, some consumers who purchase organic products in these areas might overvalue their quality. In contrast, consumers in wealthier or more educated areas may not overvalue the quality of organic products, even though many of them may still prefer organic products. However, descriptive patterns presented above do not tell us whether spatial variations in price premiums reflect consumer information or preference externalities. In addition, they do not allow us to examine the role of markups and costs, as well as any welfare consequences. For this reason, I consider a structural approach, and this approach is described in the next section.

3 Empirical Framework

This section describes my empirical model. I first present my demand model and then my supply model. Following the standard approach to estimate the demand for differentiated products (e.g., Nevo, 2001), I aggregate a given product across different stores in the same local market and focus on the pricing decision of manufacturers. This implies that retailers' margins are assumed to be zero, but marginal costs still include costs from both manufacturers and retailers, because I only observe prices charged at retailers. More details on my model are described below.

3.1 Demand

Suppose we observe $t = 1, \ldots, T$ markets, where market t is defined by county and quarter. There are $i = 1, \ldots, M_t$ consumers in each market t, and each consumer chooses product $j \in \{0, \ldots, J_t\}$ in market t.[12] Given the nature of strained baby food, consumers in my

[12]Given that a consumer is assumed to choose only one product, i can be considered as each serving occasion (of a baby food pouch or jar) among all consumers in market t, so that market size M_t is equal to the number of kids who could potentially consume baby food pouches or jars, multiplied by the total number of days when they could consume baby food pouches or jars in a given period.

analysis are essentially parents who need to decide on whether to purchase a strained baby food product for their babies. If they decide not to purchase any, a likely outside option ($j = 0$) includes cooking strained baby food at home.

The indirect utility that consumer i receives from choosing product j in market t is

$$u_{i,j,t} = x_{j,t}\beta_i + \alpha_t p_{j,t} + r_{j,t}\gamma + \xi_{j,t} + \bar{\epsilon}_{i,j,t}, \tag{1}$$

where $x_{j,t}$ is a vector of observable product characteristics, $p_{j,t}$ is the price of product j in market t, and $r_{j,t}$ is a vector of variables related to recalls I discuss below in more details. The indirect utility for outside good is given by $u_{i,0,t} = \xi_0 + \sigma_0\nu_{i,0} + \epsilon_{i,0,t}$, where ξ_0 and σ_0 are normalized to be zero.

Price premiums may also reflect the perceived quality that depends on how informed consumers are. As discussed in Section 2.3, the spatial distribution of informed consumers could underlie spatial variations in price premiums. However, it is difficult to observe both product quality and consumer's knowledge. Both could be related to advertising, but firms choose their advertising strategically. Hence, advertising may not be used to measure quality or knowledge. To address this challenge, I exploit exogenous shocks given by Plum Organics' recalls described in Section 2.1. If consumers consider recalls as a signal to unobserved adverse quality of recalled products, they may change their perception about these products. If there is group reputation or spillover, the effect of recalls may extend to other related products. These effects are incorporated by $r_{j,t}\gamma$ in (1). Specifically, I include three interaction terms, where a dummy for the post-recall period is interacted with a dummy for recalled UPCs, a dummy for the recalling firm, and a dummy for organic products in general.

In (1), β_i is a vector of random coefficients, capturing individual-specific preference for particular product characteristics. Following Berry, et al. (1995), I specify β_i as follows:

$$x_{j,t}\beta_i = x_{j,t}\beta + \sum_k \sigma_k x_{j,t,k}\nu_{i,k}, \tag{2}$$

where ν follows a known distribution P_0. In the estimation, I use random coefficients for the organic dummy variable and the constant, so that the model allows for consumer-specific preference for organic products (relative to non-organic products) as well as inside goods relative to the outside good. For the price coefficient, I assume that $\alpha_t = \alpha + \sum_a \lambda_a w_{t,a}$, where $w_{t,a}$ includes county-level income, population, and education.

The unobserved product characteristics is assumed to be $\xi_{j,t} \equiv \Delta\xi_{j,t} + FE_{j,t}$. Note that $FE_{j,t}$ includes fixed effects for DMA×year×quarter, county×year, product×region×year, and product×county, where DMA stands for Designated Market Area. In (1), $\bar{\epsilon}_{i,j,t}$ is an idiosyncratic error term following an extreme value distribution and is given by

$$\bar{\epsilon}_{i,j,t} = \zeta_{i,g,t} + (1-\rho)\epsilon_{i,j,t}, \tag{3}$$

where $\epsilon_{i,j,t}$ is the independent and identically distributed extreme value, $\rho \in [0,1)$ is a nesting parameter, and $\zeta_{i,g,t}$ has the unique distribution that allows $\bar{\epsilon}_{i,j,t}$ to follow an extreme value distribution. The specification in (3) follows the distribution assumptions of the nested logit model in Berry (1994) and Cardell (1997). For group $g \in \mathcal{G}_{g,t}$, I consider four groups: Gerber, organic products, non-organic products, and the outside good.[13] Combining the stochastic assumptions in (2) and (3) results in a random coefficient nested logit model (e.g., Grennan, 2013; Miller and Weinberg, 2017).

Consumers are assumed to choose product j that yields the highest utility. Given the indirect utility above, the probability that consumer i chooses product j is given by

$$\Pr(i \text{ at } t \text{ chooses } j \in \mathcal{G}_{g,t}) = \frac{\exp(\delta_{i,j,t}(\nu_i)/(1-\rho))}{D_{g,t}} \frac{D_{g,t}^{1-\rho}}{\sum_{\mathcal{G}_{g,t} \subset J_t} D_{g,t}^{1-\rho}},$$

where $\delta_{i,j,t}(\nu_i) = x_{j,t}\beta + \sum_k \sigma_k x_{j,t,k}\nu_{i,k} + \alpha_t p_{j,t} + r_{j,t}\gamma + \xi_{j,t}$, and $D_{g,t}$ is given by

$$D_{g,t} = \sum_{h \in \mathcal{G}_{g,t}} \exp(\delta_{i,h,t}(\nu_i)/(1-\rho)).$$

Integrating ν_i out in the probability above yields the market share of product j as

$$s_{j,t} = \int \frac{\exp(\delta_{i,j,t}(\nu_i)/(1-\rho))}{D_{g,t}} \frac{D_{g,t}^{1-\rho}}{\sum_{\mathcal{G}_{g,t} \subset J_t} D_{g,t}^{1-\rho}} P_0(d\nu). \tag{4}$$

The demand model in (4) is estimated by using a generalized method of moments (GMM) method, based on the moment conditions from instrumental variables. To implement the estimation, I use PyBLP developed by Conlon and Gortmaker (2020). I consider two sets of instruments. The first includes differentiation instruments developed by Gandhi and Houde (2017). These instruments improve upon the standard BLP instruments (Berry, et al., 1995)

[13] I consider a separate group for Gerber, because it is the dominant firm, and it is also the only firm in my data that offers both organic and non-organic products.

by using only similar products' characteristics to construct instruments. The second is based on exogenous shocks from recalls. Recalls increase the one-time cost required to process recall and refund. Moreover, the market share of recalled products significantly drops immediately after the recall, as defective products are removed from the market. Their market shares tend to rise quickly, as recalled UPCs are replaced by the same UPCs devoid of defects. These variations essentially provide a supply shifter in the very short term. As a result, I create a dummy equal to 1 if product j is recalled and time t is within one quarter after the recall. This variable is used as the second type of instrument.

3.2 Supply

Firm f's profit at market t, $\Pi_{f,t}$, is given by

$$\Pi_{f,t} = \sum_{j \in \mathcal{F}_{f,t}} (p_{j,t} - c_{j,t}) M_t s_{j,t}(p) - F_{f,t},$$

where $\mathcal{F}_{f,t}$ is the set of products produced by firm f in market t, $c_{j,t}$ is the marginal cost, and $F_{f,t}$ is firm f's fixed costs at market t. In this paper, I do not attempt to identify fixed costs which determine a firm's decision to enter a market or offer a product. Instead, this paper focuses on a firm's pricing decision. Though a firm's entry or product offering decision can be also important, it is not modeled in this paper, because the main focus of this paper is to examine potential sources behind spatial variations in prices that can be explained even without any information on fixed costs.

The key information required for my analysis is markups and marginal costs. To recover them, I assume a Bertrand-Nash equilibrium in prices, and consider the following first-order condition for the price that maximizes the profit function above.

$$s_{j,t}(p) + \sum_{h \in \mathcal{F}_f} (p_{h,t} - mc_{h,t}) \frac{\partial s_{h,t}(p)}{\partial p_{j,t}} = 0. \tag{5}$$

I recover marginal costs by using (5) and demand estimates. Specifically, inverting (5) gives an expression for markups in terms of $s_{j,t}$ and $\frac{\partial s_{r,t}(p)}{\partial p_{j,t}}$, $\forall j, r = 1, \ldots, J_t$. Marginal costs can be computed by using these markups and observed prices.

There are also other approaches to recover markups and marginal costs. One is to use total costs from accounting. However, this does not separate costs for different products in different markets, and total costs combine both marginal costs and fixed costs. Another approach is to use wholesale prices as marginal costs, and compute markups as the difference between the retailer's price and the wholesale price. However, the data on wholesale prices are not publicly available, and often wholesale prices are available from only one wholesaler. The most critical issue of this approach is that it ignores other types of retailers' marginal costs (e.g., distribution costs) and also disregards both markups and costs of manufacturers. One more approach is to use production data (e.g., De Loecker and Warzynski, 2012). However, this requires detailed production data that are not publicly available. In addition, even restricted census data on plant-level production do not provide information on inputs for different products sold in different geographic markets. As a result, I instead rely on the standard approach in industrial organization (e.g., Nevo, 2001) to recover marginal costs and markups.

4 Results

This section first present the demand model estimates. I then discuss recovered markups and costs, and examine how much markups vs. costs can explain price premiums of organic products. I further explore potential sources behind spatial variations in price premiums, using the estimated model and counterfactual simulations.

4.1 Demand Model Estimates

Table 2 presents the demand estimates from a GMM estimation of the model in Section 3.1. These estimates are estimated by controlling for several types of fixed effects. The table shows that the coefficient estimate on price is negative and precisely estimated. However, the coefficients on the price interactions with county-level demographics are mostly not estimated precisely, possibly because county-year fixed effects are included in the estimation. The coefficient estimates on recall-related variables are negative, indicating that consumers do not prefer recalled products as well as the recalling firm's other products after recalls. All coefficients on observed product characteristics and random coefficients are significant. Lastly, the coefficient on the nesting parameter is 0.204 and estimated precisely. This estimate suggests that correlation in preferences for products of the same group is not too strong, thus potentially increasing consumer substitution across groups (particularly between the inside and outside goods).

Using the estimated demand and the first-order condition in (5), I recover marginal costs of all products sold in each local market. Figure 10 shows the distribution of marginal costs in the bottom figure. As a comparison, Figure 10 also plots the histogram of observed prices in the top figure. The top figure shows that prices for organic products (in blue) tend to be higher than prices for non-organic products (in red). In addition, organic prices have much larger variance than non-organic prices. The bottom figure is similar to the top figure, even though most values in the bottom figure are smaller than those in the top figure, suggesting that the key patterns in organic vs. non-organic prices may closely reflect the patterns in organic vs. non-organic marginal costs. In other words, organic prices are higher than non-organic prices, likely because marginal costs for organic products are higher than those for non-organic products.

To further examine the role of markups in price differences, Figure 11 plots the histogram of markups for organic products (in blue) and non-organic products (in red), where markups are defined to be $(p - c)/p$. Surprisingly, markups for organic products tend to be lower than those for non-organic products. Therefore, organic products are more expensive than non-organic products not because of higher markups, but due to higher costs of organic products. Given relatively lower markups of most organic brands, it is also unlikely that most consumers overvalue the quality of new organic premium brands. Though this finding may appear to be surprising, higher markups require market power, and at least in the baby food industry, most organic firms are small or medium-sized, compared to Gerber which mainly produces non-organic products and is dominant not only in the national market but also in most local markets. This suggests that market power of most organic firms may be weaker than Gerber's market power, which could also explain lower markups of organic products.

4.2 Decomposing Spatial Variations in Organic Premium

Using the estimated marginal costs and markups for each product in each market, I compute the county-level quarterly quantity-weighted average marginal costs and markups for organic products and non-organic products. County-level costs and markups over the county-level fraction of college graduates are plotted in Figure 12, which is similar to Figure 4, except that the y-axis is costs in the top figure and markups in the bottom figure. The top figure shows that marginal costs tend to be lower in more educated counties than less educated counties. Though organic products' marginal costs are generally higher than non-organic products' marginal costs in most areas, organic marginal costs in more educated areas are much lower than those in less educated areas, relative to non-organic marginal costs. Table 3 reports the gradient of the fitted line, which indicates that if a county has more college graduates than another county by 10 percentage points, its difference in marginal costs between organic and non-organic products would be smaller by \$0.03, compared to another county.

The bottom figure in Figure 12 reveals that markups, measured by $p - c$, tend to be higher in more educated counties than less educated counties for both organic and non-organic products. However, non-organic products' markups in more educated areas are much higher than those in less educated areas, relative to organic products' markups. Table 4 reports the gradient of the fitted line. It shows that if a county has more college graduates than another county by 10 percentage points, its difference in markups between non-organic and organic products would be larger by \$0.018, compared to another county.

In Panel A of Table 5, I summarize these gradients with respect to the fraction of college graduates. Given that Δprice = Δcost + Δmarkup, the table suggests that a decrease in price premiums with respect to the fraction of college graduates can be explained by a decline in $c^o - c^n$ by 62% ($= \frac{-0.305}{-0.488}$) and by a decline in $\mu^o - \mu^n$ by 38% ($= \frac{-0.183}{-0.488}$). In Panel B, I consider the log of county-level median household income, and repeat the same calculations above. According to the table, a decrease in price premiums with respect to county income can be explained by a decline in $c^o - c^n$ by 72% ($= \frac{-0.102}{-0.141}$) and by a decline in $\mu^o - \mu^n$ by 28% ($= \frac{-0.040}{-0.141}$). These results suggest that spatial variations in price premiums for organic baby food products are largely explained by spatial variations in marginal costs.

4.3 Counterfactual Analysis

This section considers counterfactual simulations to explore potential mechanisms that underlie spatial variations in price premiums for organic products. To this end, I examine two counterfactual scenarios. In the first scenario, all organic firms, except for Gerber organic, maximize their join profit. Under this counterfactual, the same firms currently in the market will still remain in each market, but competition between organic firms will be removed. These firms will choose prices that maximize their join profit, not their own profit. As a result, their markups will be increased, and market shares will be reallocated to more efficient organic firms with lower marginal costs in each market.

The second counterfactual removes all organic firms, except for Gerber organic. This counterfactual examines what would happen if these firms had not entered the market. This eliminates not only competition among organic firms, but also any effect of entry, including competition with the dominant firm, reallocation of market shares to efficient entrants, and potential market expansion from entry. In each counterfactual, I compute new equilibrium prices and market shares for each market. Under both counterfactuals, changes in market outcomes are more likely in markets with more organic firms.

Figure 13 plots county-level quarterly prices over the fraction of college graduates under three cases. The first case is an "old" equilibrium from the data (in the top figure), which is the same as Figure 4. The second is a new equilibrium from the first counterfactual (in the middle figure). The third case is a new equilibrium from the second counterfactual (in the bottom figure). Comparing the first case and the second case reveals that eliminating competition among organic products reduces spatial differences in price premiums for organic products. To quantify the change, Table 6 reports the gradient under three cases. Comparing column 1 between Panel A (from data) and Panel B (from the first counterfactual) indicates that removing competition among organic firms alone reduces spatial variations in organic premiums by about 44% ($= \frac{-0.488+0.274}{-0.488}$).

Comparing the second case and the third case in Figure 4 as well as Table 6 shows that removing other types of competition, for example, between Gerber and other organic firms, decreases spatial differences in organic premiums only by 12% ($= \frac{-0.274+0.213}{-0.488}$). However, even after all organic firms, except for Gerber organic, are removed from the market, spatial variations in price premiums still remain. In the second counterfactual, there is no spatial variation in terms of competition and local market structure related to organic products, since Gerber organic is the only firm offering organic products in all local markets. Accordingly, any remaining spatial variations are likely to result from variations in costs across markets. Given that the same organic firm produces organic products in all local markets, spatial variations in costs are unlikely to stem from production costs, but more likely to come from distribution costs such as costs associated with transportation or warehousing. For this reason, I conclude that the remaining spatial difference in price premiums over education ($43.6\% = \frac{-0.213}{-0.488}$) can be explained by spatial differences in distribution costs.

To further examine welfare implications, I compute consumer surplus and producer surplus in terms of variable profits under three cases. Figure 14 plots their changes from an old equilibrium to a new equilibrium. The top figure shows that the first counterfactual slightly increases variable profits across markets, whereas the second counterfactual significantly reduces variable profits much more in more educated markets. This suggests that profits earned by organic firms are likely to result from market expansion, rather than stealing business from the dominant firm's organic business, and the market expansion effect is stronger in more educated markets.

The bottom figure of Figure 14 reveals that both counterfactuals reduce consumer surplus, but the decline in consumer surplus under the second counterfactual is much more significant than that under the first counterfactual. This suggests that consumers benefit more from entry than price competition. The figure also shows that the reduction in consumer surplus is larger in more educated markets, implying that consumers in more educated areas derive greater benefits from organic products than those in less educated areas.

In Figures 15-16, as well as Table 7, I consider the log of county-level median household income, instead of the county-level fraction of college graduates. They show similar results as above, suggesting that similar conclusions can be drawn in terms of spatial variations in income. Lastly, I consider one more counterfactual where Plum Organics did not have recalls. However, this counterfactual did not produce any significant change in prices or any market outcomes, suggesting that the role of consumer information captured by recalls may not be important in explaining spatial variations in price premiums. These findings therefore emphasize the critical roles of local market structures and cost structures in shaping spatial variations in price premiums, consumer welfare, and market efficiency.

5 Conclusion

This paper investigates the roles of markups and costs in explaining the higher prices of high-quality products and explores why price premiums for these products are lower in wealthier or more educated areas. Using scanner data on baby food prices and quantities, I document that organic products generally command substantial price premiums over non-organic alternatives, but these premiums decline with county-level income, population, and education. By estimating a random coefficient nested logit demand model and assuming Bertrand-Nash pricing, I recover product-specific markups and costs across local markets. I find that organic products typically have higher costs but lower markups compared to non-organic products. For both products, markups increase and costs decrease with county-level income and education. For organic products, however, the increase in markups is less pronounced, while the decrease in costs is more pronounced, aligning with the observed spatial variation in premiums. Counterfactual analysis reveals that removing competition among organic products reduces spatial differences in organic premiums by about half, mainly due to increased markups in richer or more educated areas. Spatial differences in costs, likely tied to distribution rather than production, explain the remaining price variations. Additionally, wealthier or more educated areas benefit more from organic products due to higher consumer surplus and variable profits. These findings underscore the role of local market structures on spatial variations in price premiums, consumer welfare, and market efficiency.

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Appendix: Data

The RMS data provide each UPC's product characteristics, particularly including information on USDA organic seal and organic claim. I use these variables to define organic products. Specifically, I define a dummy variable for USDA organic to be 1 if *usda_organic_seal_descr* includes "USDA ORGANIC SEAL" or its slight variations (e.g. "ORGANIC USDA"), but without "NO" or "NOT" (e.g. "NO USDA"). A dummy variable for organic claim is defined to be 1 if *organic_claim_descr* includes "ORG" (Organic), "QAI" (Quality Assurance International Organic Certification), "CO" (Certified Organic), or their minor variations. I define organic to be equal to 1 if if USDA organic or organic claim is equal to 1.

In the strained baby food module, there are several hundreds of UPCs in each year. For the same brand, there are multiple UPCs reflecting different sizes or flavors. I aggregate them by county, quarter, and product. Products are major brands based on "brand description" in the RMS data. In the strained baby food module, there are many brands with only a small number of UPCs, whereas a majority of UPCs belong to a small number of major brands. As discussed in Section 2.2, I consider 8 major brands for products, and these products (e.g. Plum Organics) include other brands of the same firm (e.g. Plum Organics Baby). These 8 products account for 95% of total sales during my sample period. Other organic and non-organic products account for the remaining 5% of total sales.

Each product includes multiple UPCs, and the number of UPCs in each product in different county or quarter may not be the same. I use the number of UPCs as one of product characteristics. Additional product characteristics that I use include the number of flavors, and the product type (e.g. fruit, vegetable, dinner, etc.). I create quarterly prices for each product by dividing the dollar sales by the number of servings sold (deflated by CPI). Quantities are volumes divided by the modal size in this module. Market shares are defined by dividing quantities by the total potential number of servings in a county in a quarter, where I assume that every child could potential eat 5 pouches per week, so that the total potential number of servings is equal to the number of children aged 0 to 9 in each county[14], multiplied by 5 times the number of weeks in each quarter.

[14] The ACS provides the county-level number of population aged 0 to 4 as well as 5 to 9. Some children aged above 4 may still consume baby food pouches, and so I combine both age groups.

Figure 1: County-level Prices of Organic vs. Non-organic Baby Food over Income

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over county-level median household income.

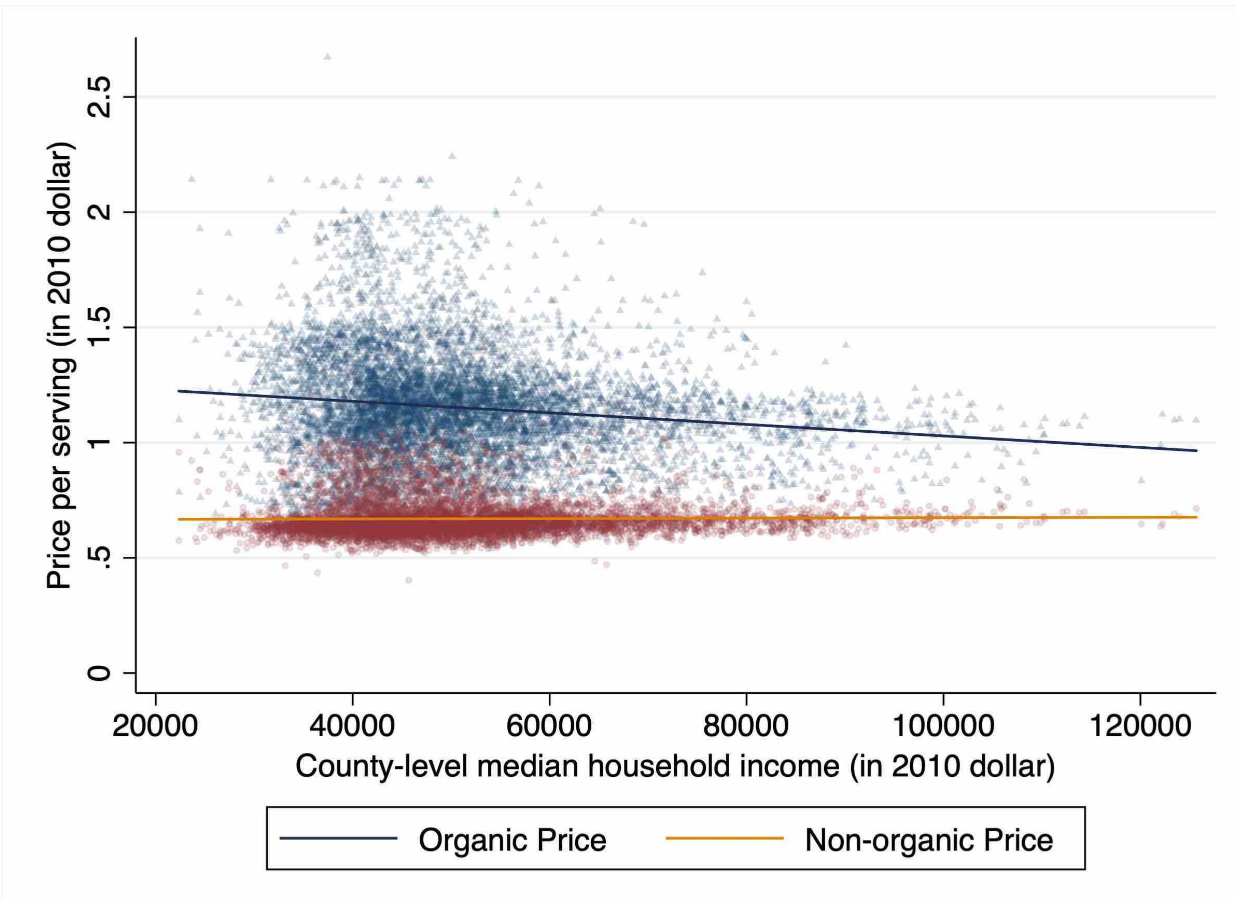
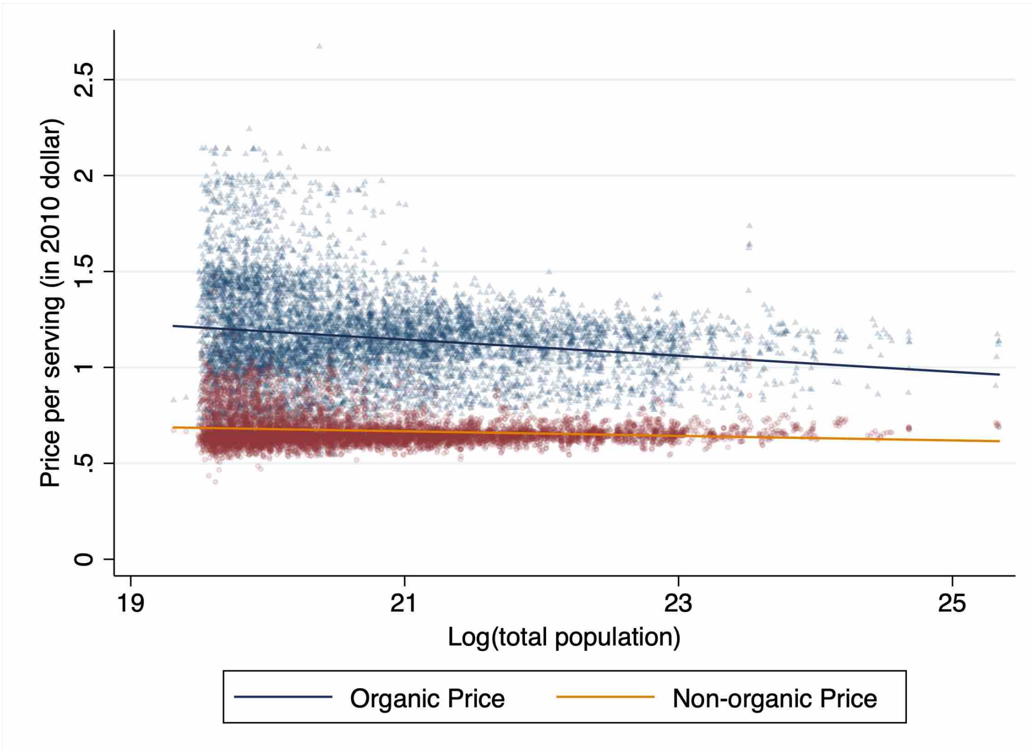


Figure 2: County-level Prices and Population

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over county-level total population (top figure) and population aged 0-9 (bottom figure).



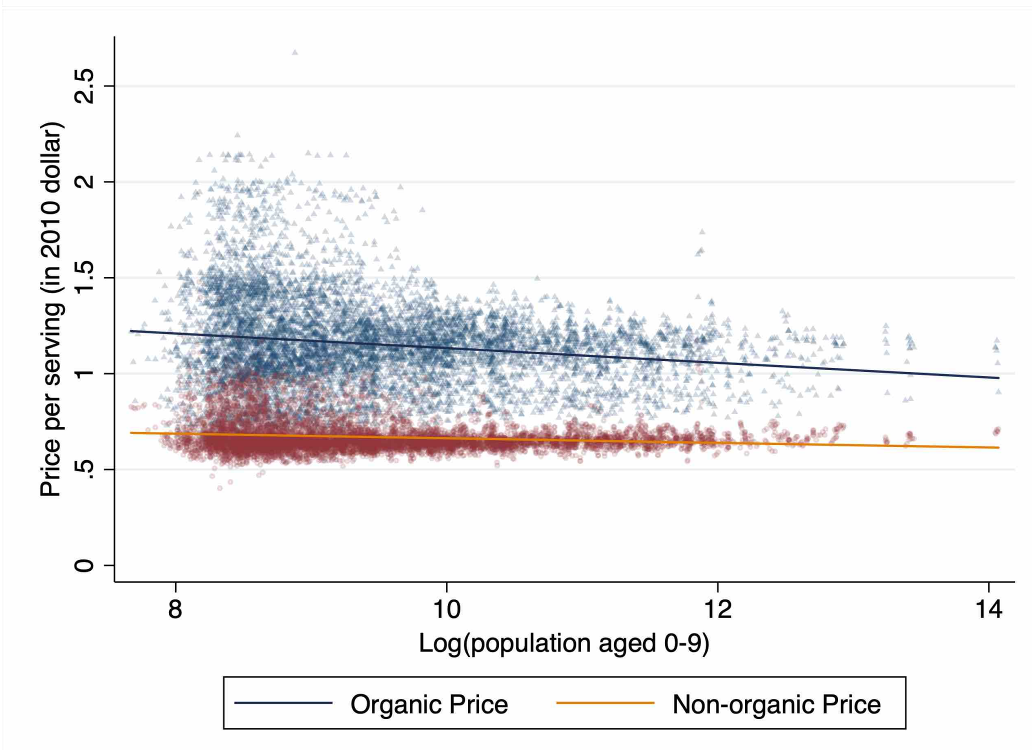


Figure 3: County-level Prices and the Log Income

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over the log of county-level median household income.

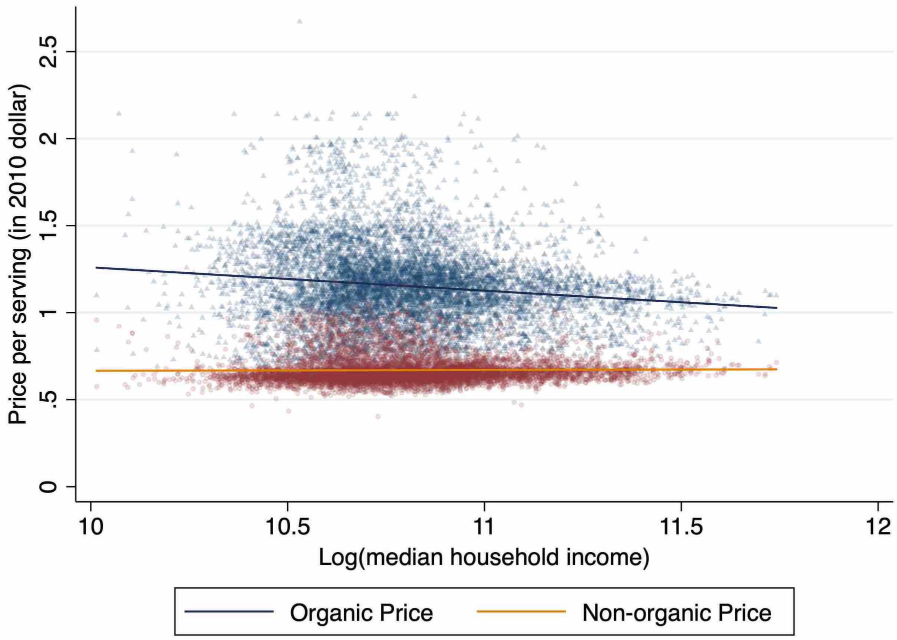


Figure 4: County-level Prices and Education

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over county-level fractions of college graduates.

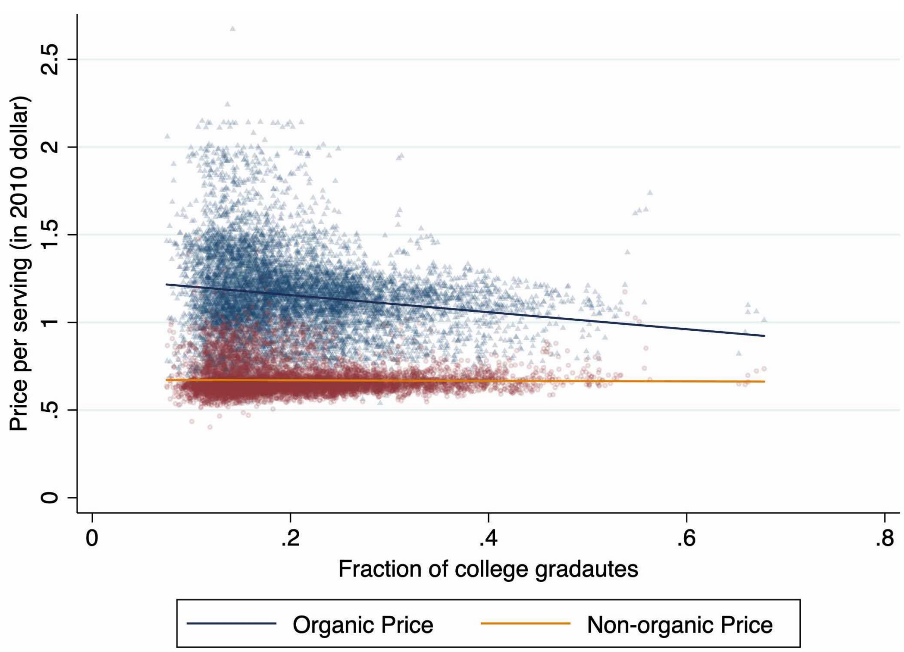


Figure 5: County-level Market Shares and Education

Notes: The figure plots county-level quarterly market shares for organic vs. non-organic baby food among inside goods over county-level education.

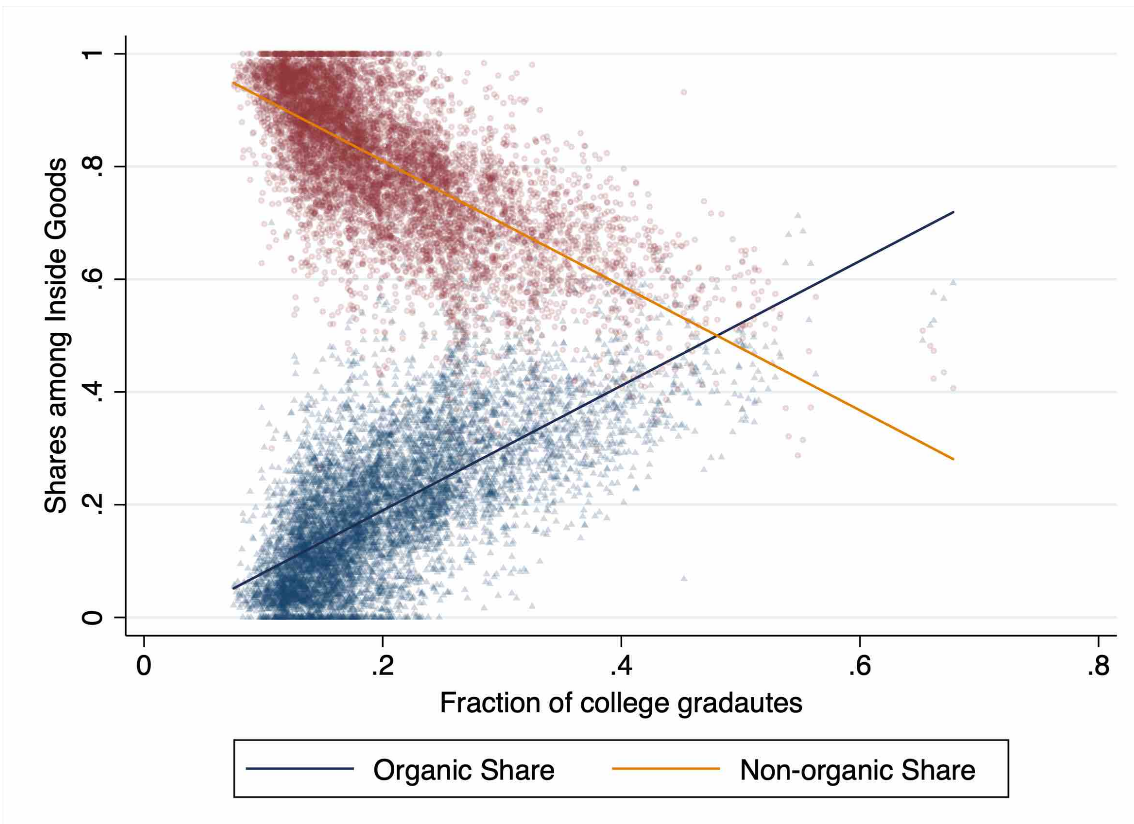


Figure 6: County-level #Products and Education

Notes: The figure plots county-level #UPCs (top figure) and #flavors (bottom figure) for organic vs. non-organic baby food over the county-level fraction of college graduates.

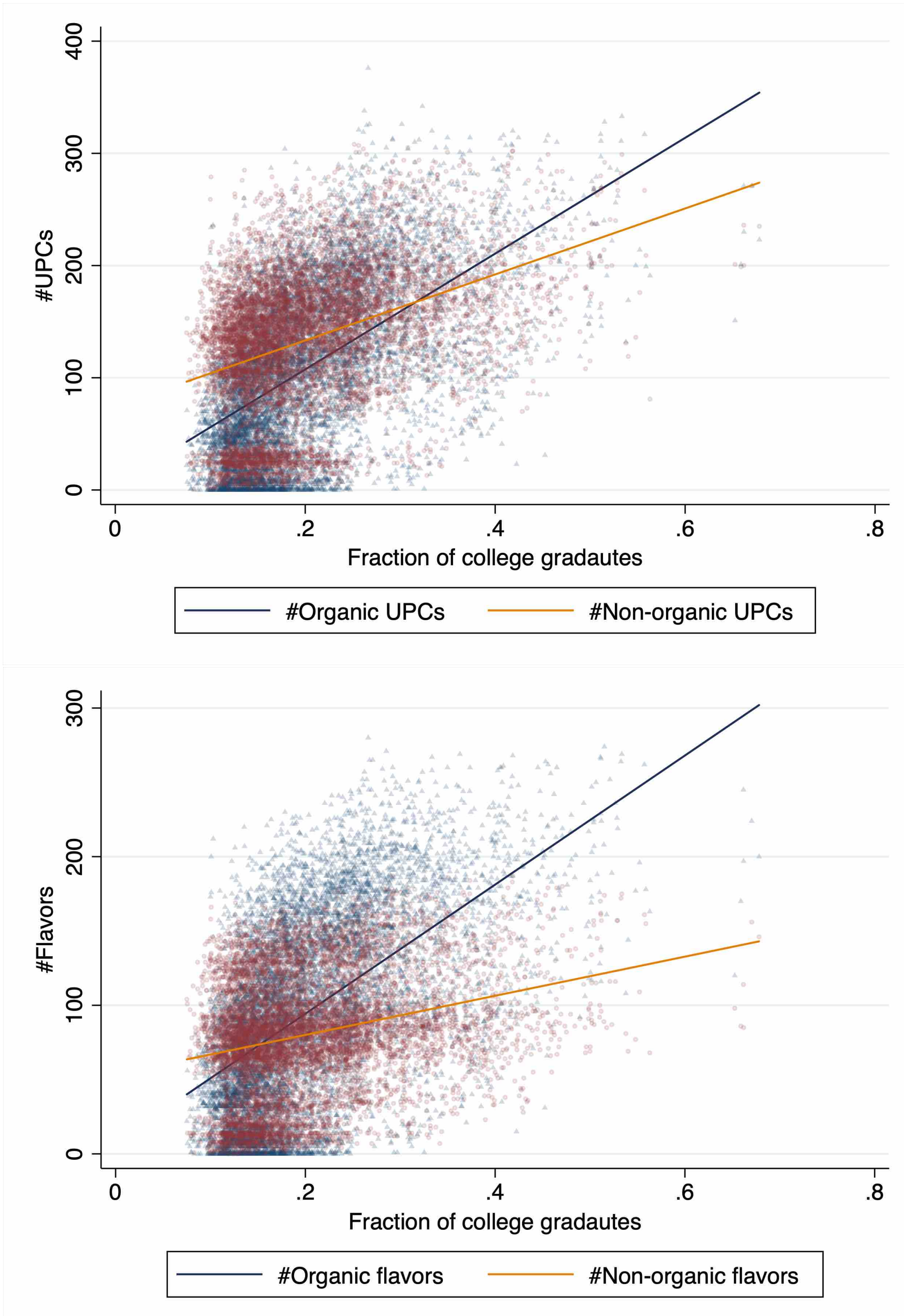


Figure 7: County-level Revenues and Education

Notes: The figure plots the log of county-level quarterly revenues (deflated by using CPI) for organic vs. non-organic baby food (top figure) and for all baby food (bottom figure) over county-level fraction of college graduates.

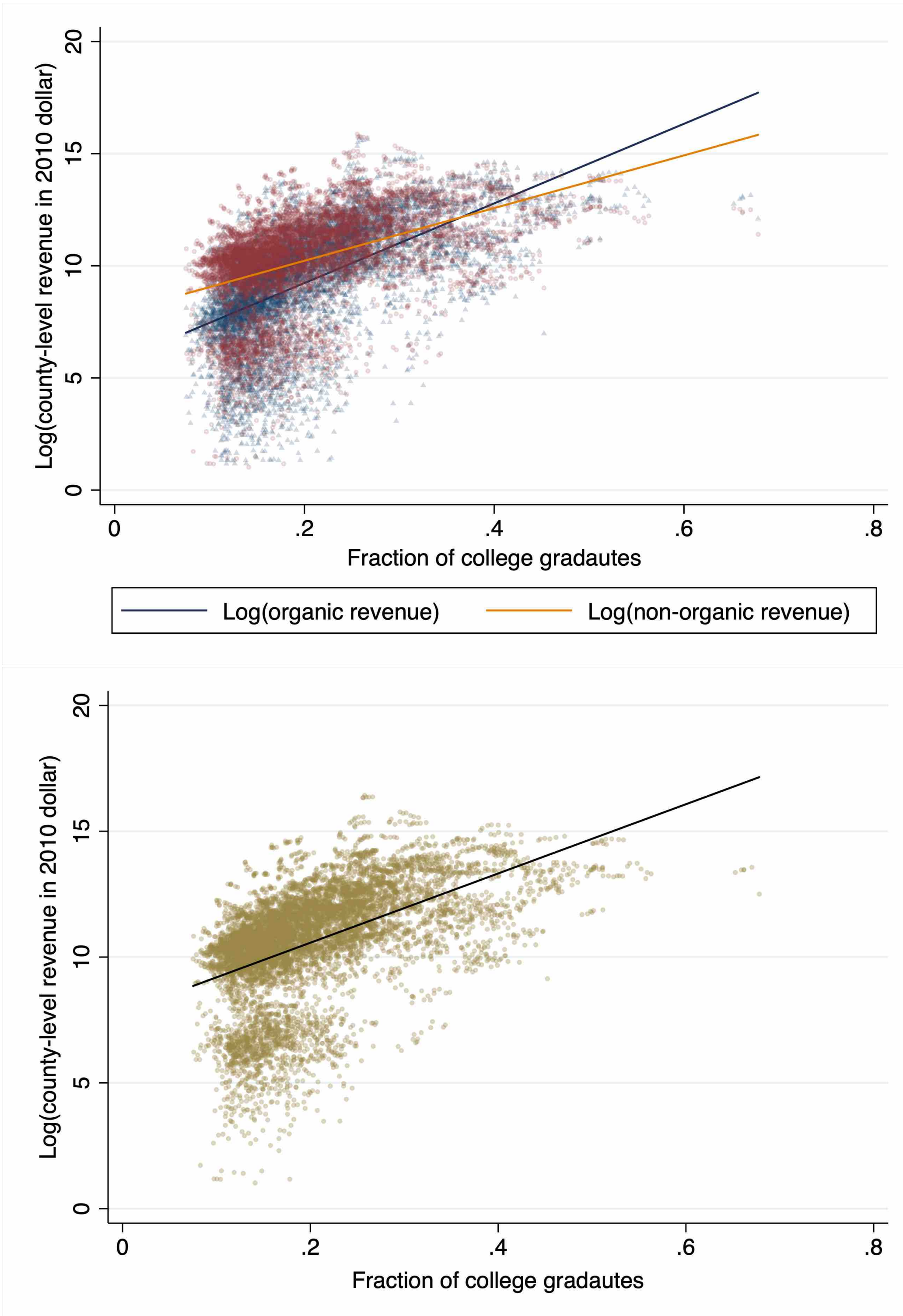


Figure 8: County-level Market Concentration and Education

Notes: The figure plots Herfindahl-Hirschman Index for quarterly county baby food markets.

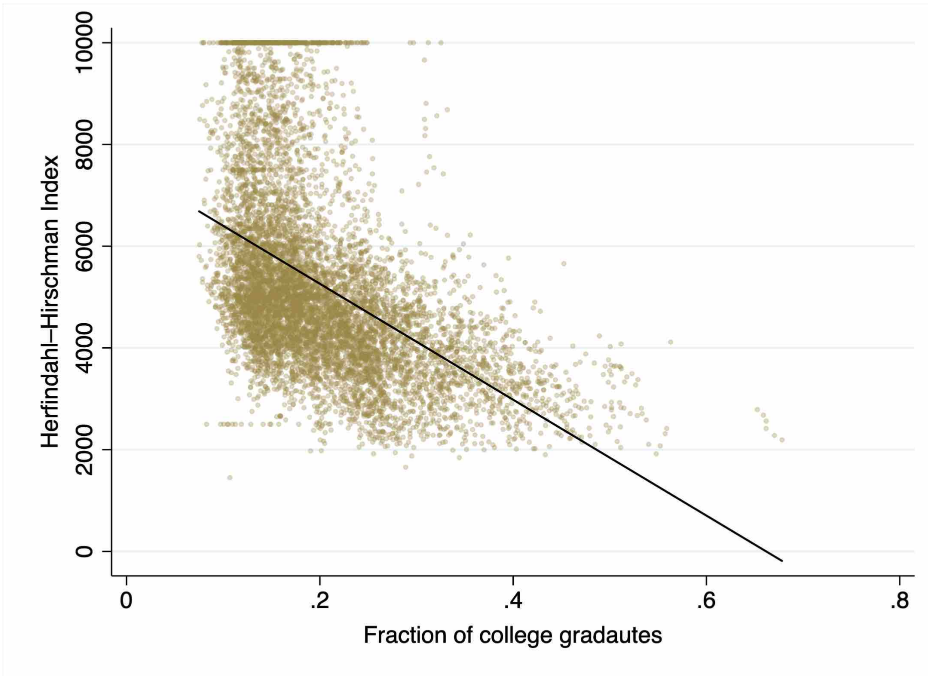


Figure 9: County-level Prices and Market Concentration

Notes: The figure plots county-level quarterly prices for organic vs. non-organic baby food over HHI.

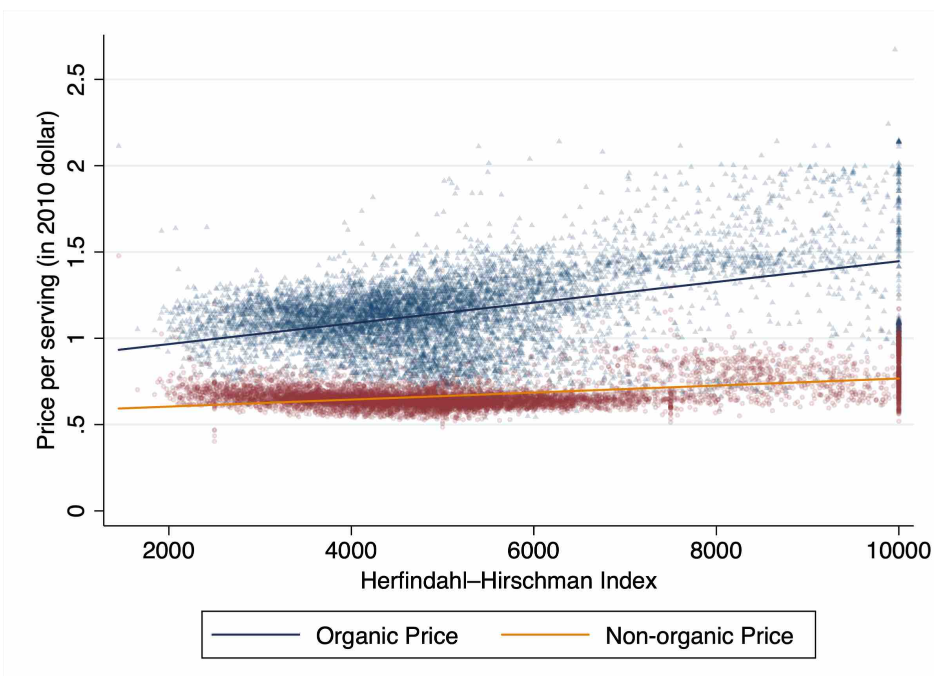
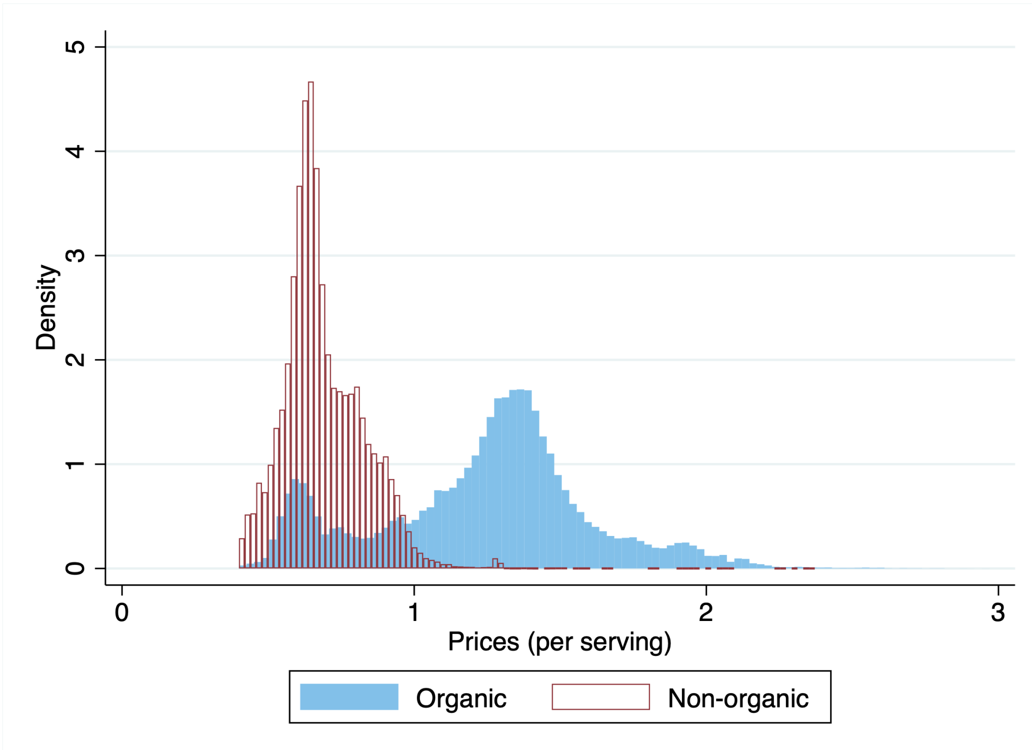


Figure 10: Prices and Marginal Costs for Organic vs. Non-organic Baby Food

Notes: The figure plots the histogram of CPI-deflated quarterly prices (top figure) and marginal costs (bottom figure) for organic vs. non-organic baby food products.



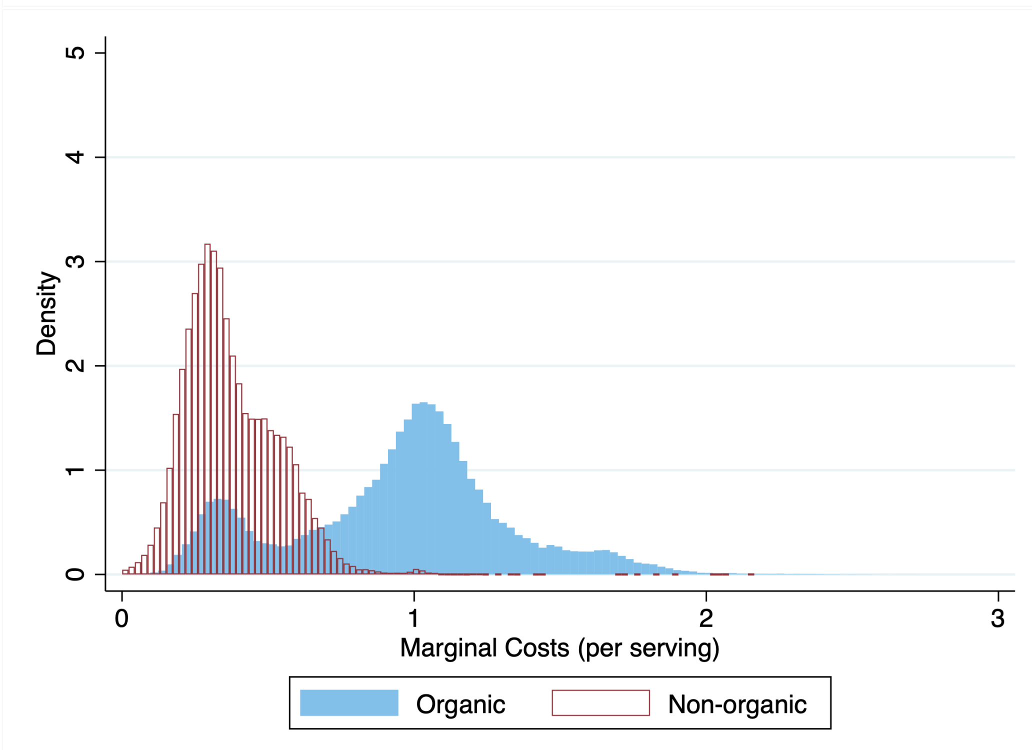


Figure 11: Markups for Organic vs. Non-organic Baby Food

Notes: The figure plots the histogram of markups for organic vs. non-organic baby food products, where markups are defined to be (price − cost)/price.

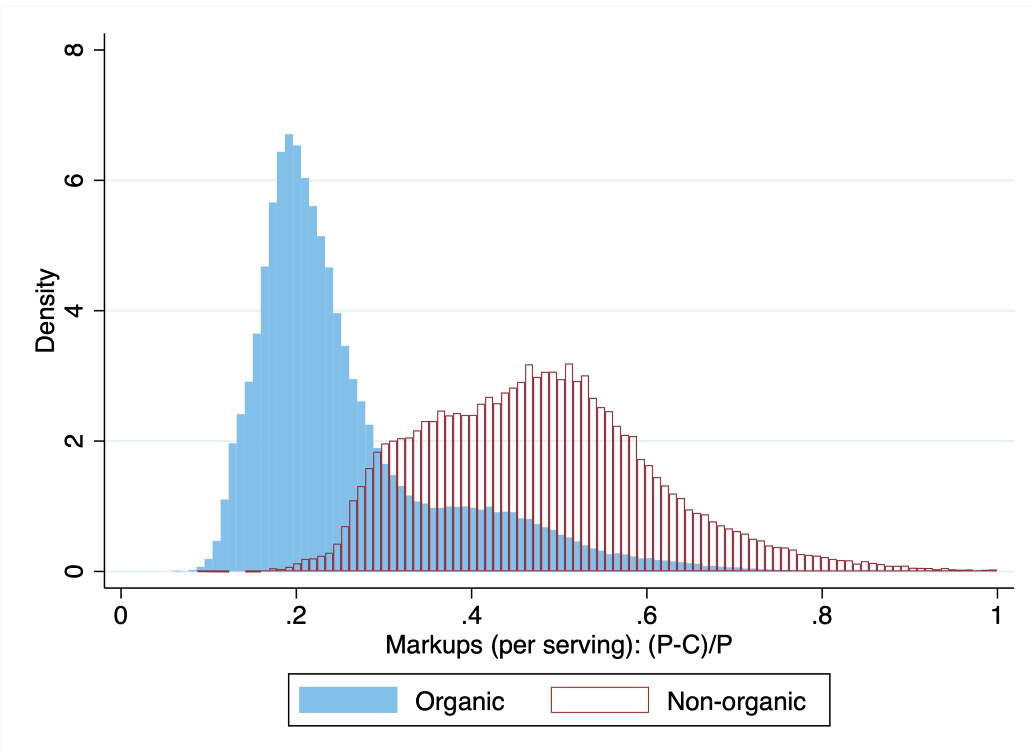


Figure 12: County-level Marginal Costs and Markups over Education

Notes: The figure plots county-level marginal costs (top figure) and markups (bottom figure) for organic vs. non-organic baby food over the county-level fraction of college graduates, where markups = price − cost.

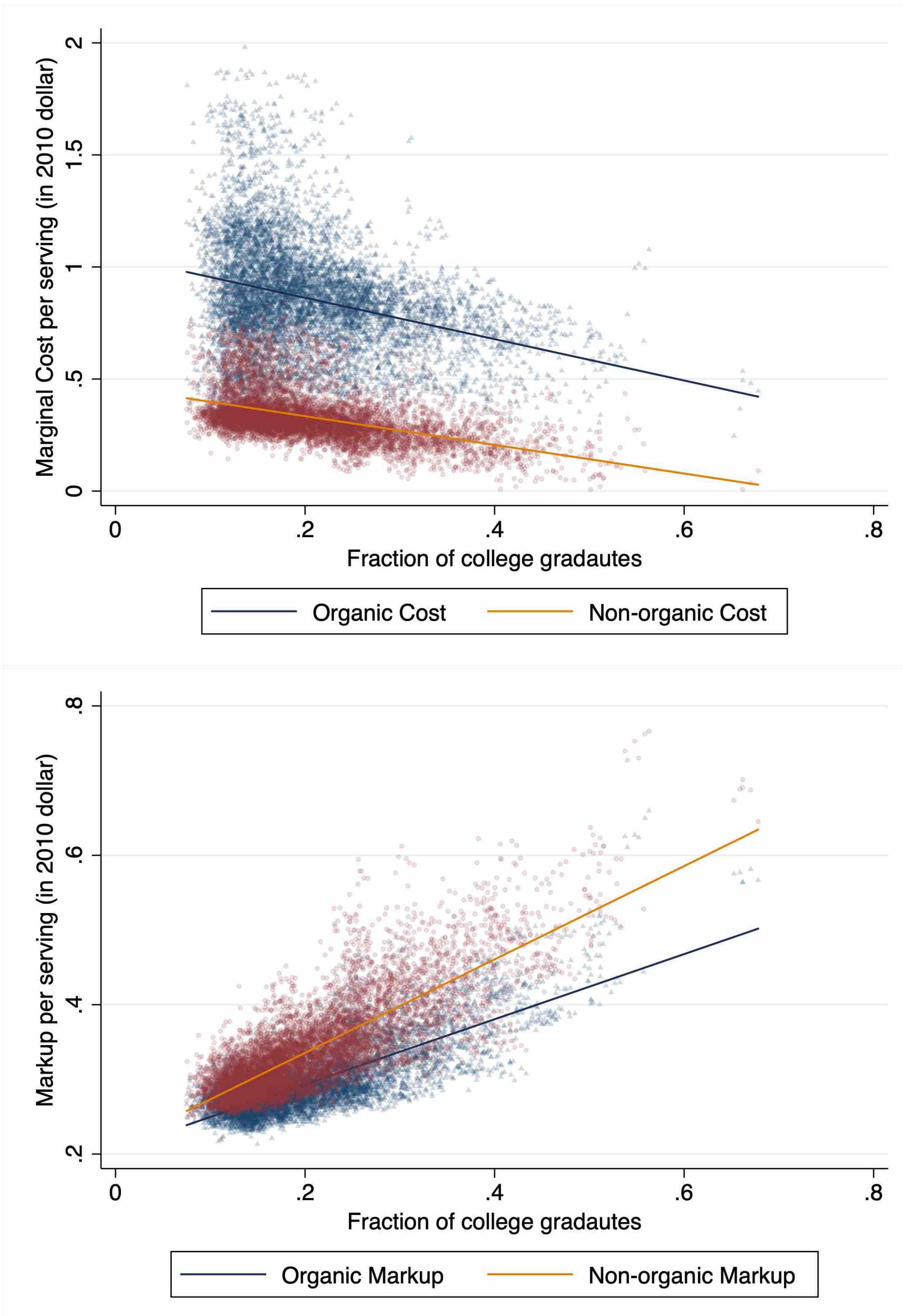


Figure 13: County-level Prices over Education under Counterfactual Equilibrium

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over county-level fractions of college graduates under initial equilibrium (top figure), counterfactual equilibrium for joint profit maximization among organic firms (middle figure), and counterfactual equilibrium for no organic firms (bottom figure).

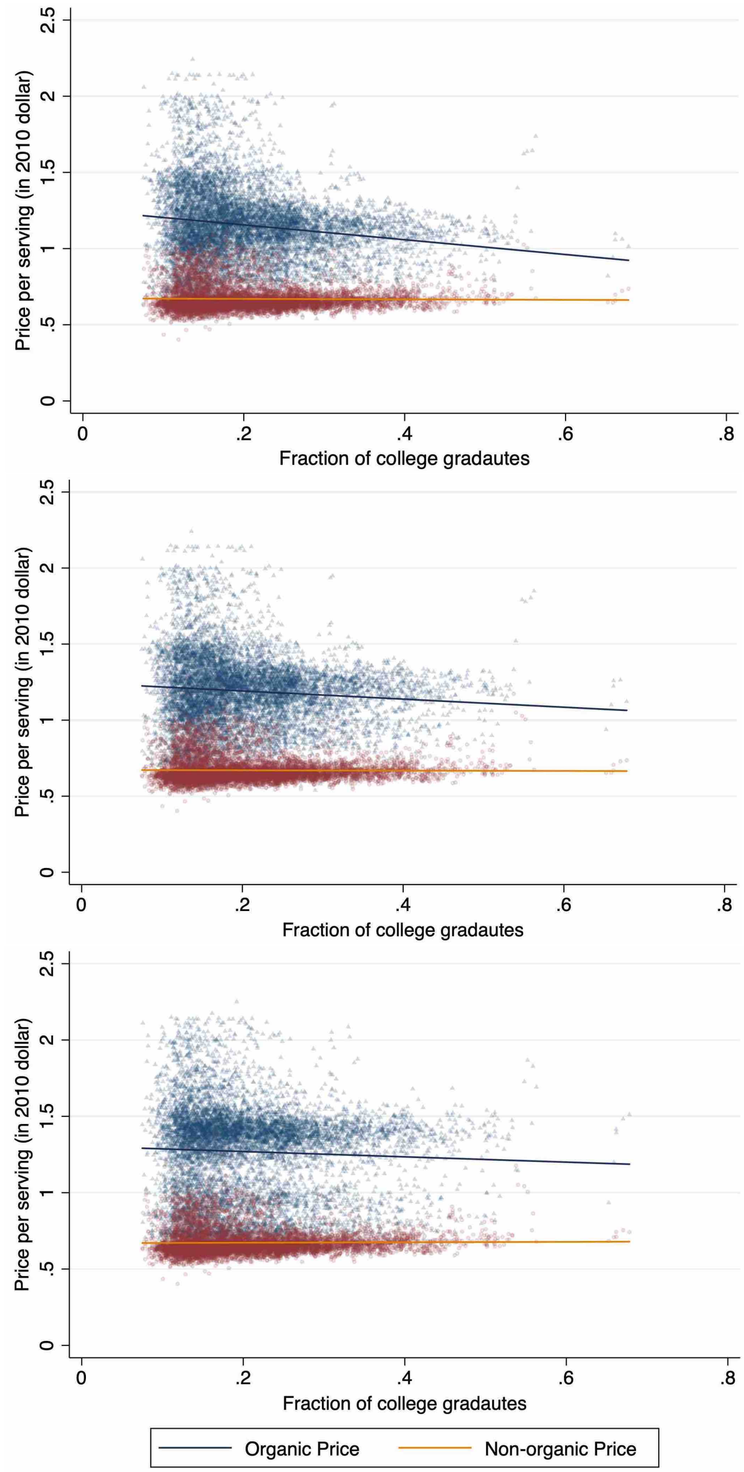
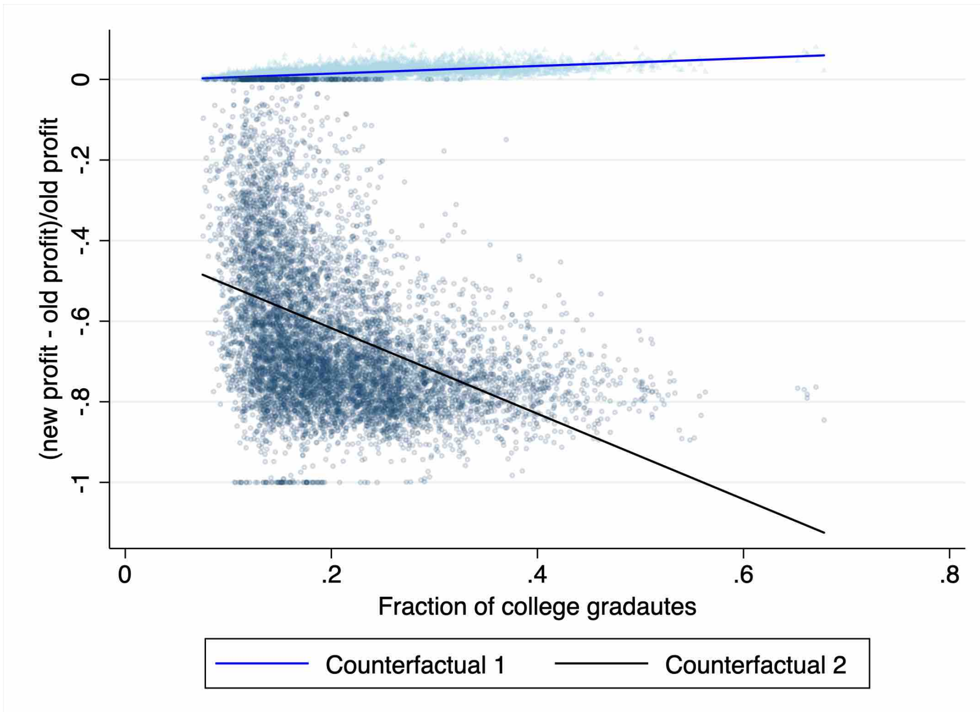


Figure 14: County-level Profit and Consumer Surplus over Education under Counterfactual

Notes: The figure plots county-level changes in profits (top figure) and changes in consumer surplus (bottom figure) over the county-level fraction of college graduates under counterfactual 1 with joint profit maximization among organic firms and counterfactual 2 with no organic firms, where changes in profits = (profits under counterfactual equilibrium − profits under initial equilibrium)/profits under initial equilibrium, and changes in consumer surplus = (CS under counterfactual equilibrium − CS under initial equilibrium)/CS under initial equilibrium.



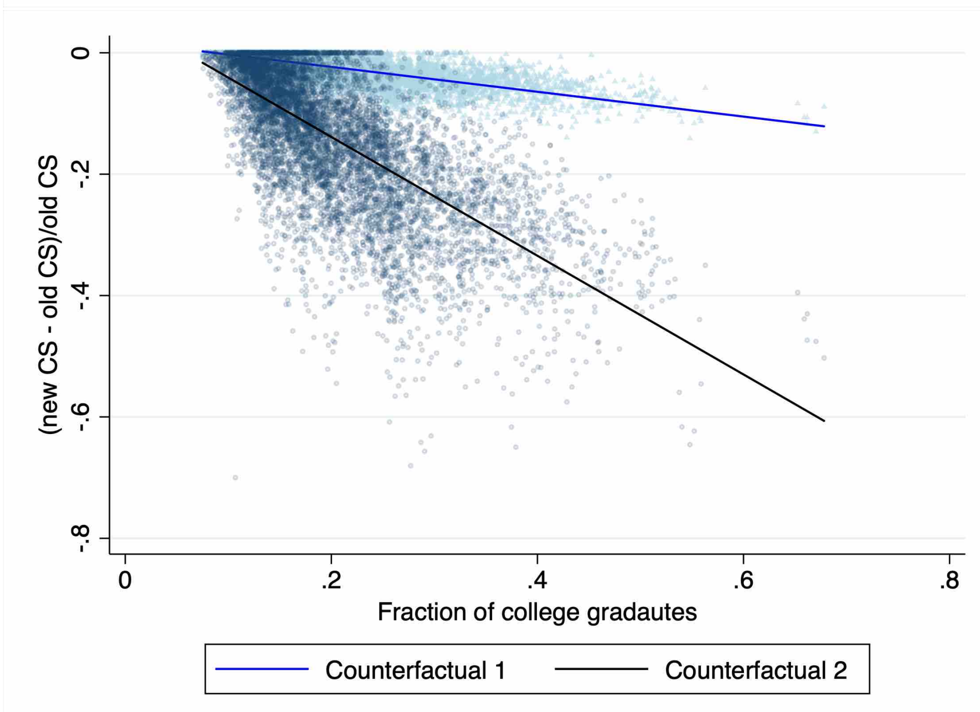


Figure 15: County-level Prices over Income under Counterfactual Equilibrium

Notes: The figure plots county-level quarterly average prices (deflated by using CPI) for organic vs. non-organic baby food over the log of county-level median household income under initial equilibrium (top figure), counterfactual equilibrium for joint profit maximization among organic firms (middle figure), and counterfactual equilibrium for no organic firms (bottom figure).

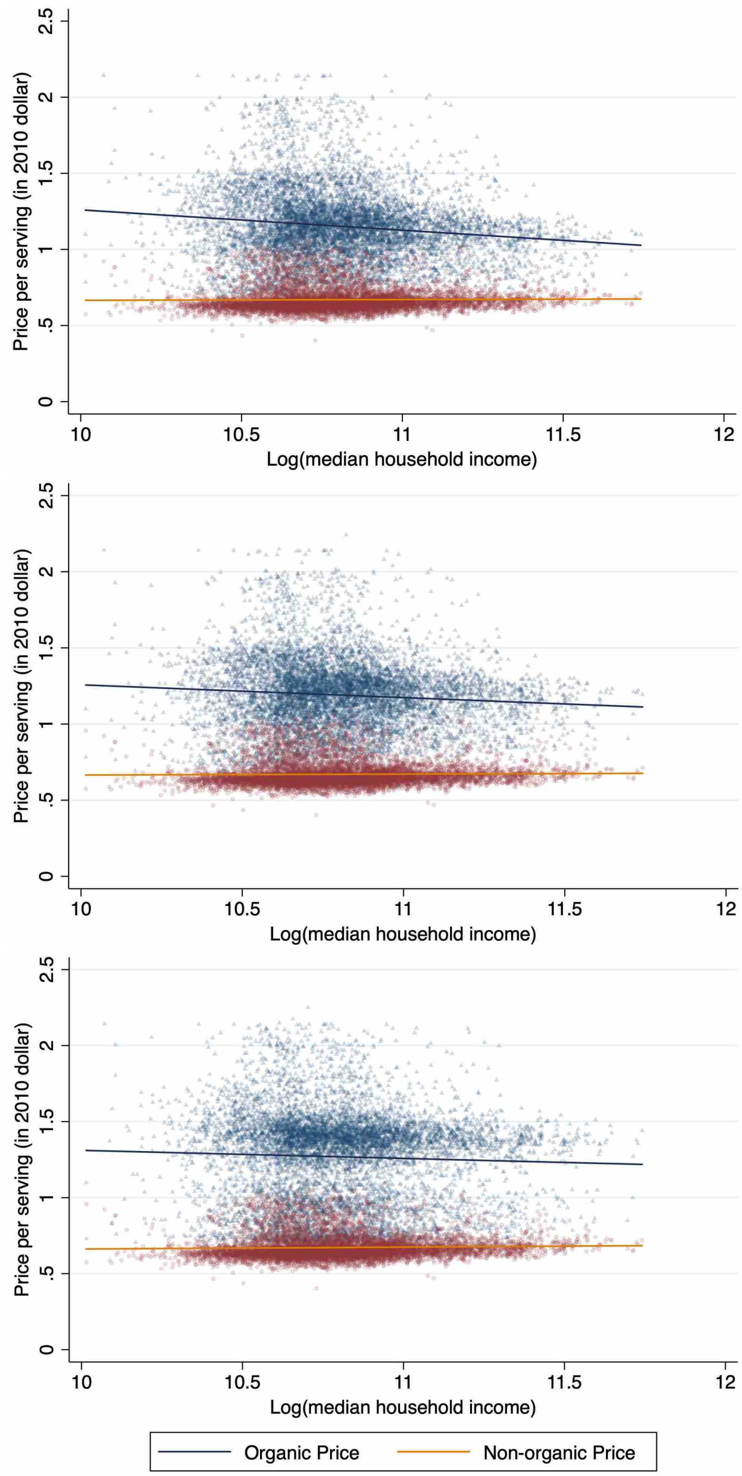


Figure 16: County-level Profit and Consumer Surplus over Income under Counterfactual

Notes: The figure plots county-level changes in profits (top figure) and changes in consumer surplus (bottom figure) over the log of county-level median household income under counterfactual 1 with joint profit maximization among organic firms and counterfactual 2 with no organic firms, where changes in profits = (profits under counterfactual equilibrium − profits under initial equilibrium)/profits under initial equilibrium, and changes in consumer surplus = (CS under counterfactual equilibrium − CS under initial equilibrium)/CS under initial equilibrium.

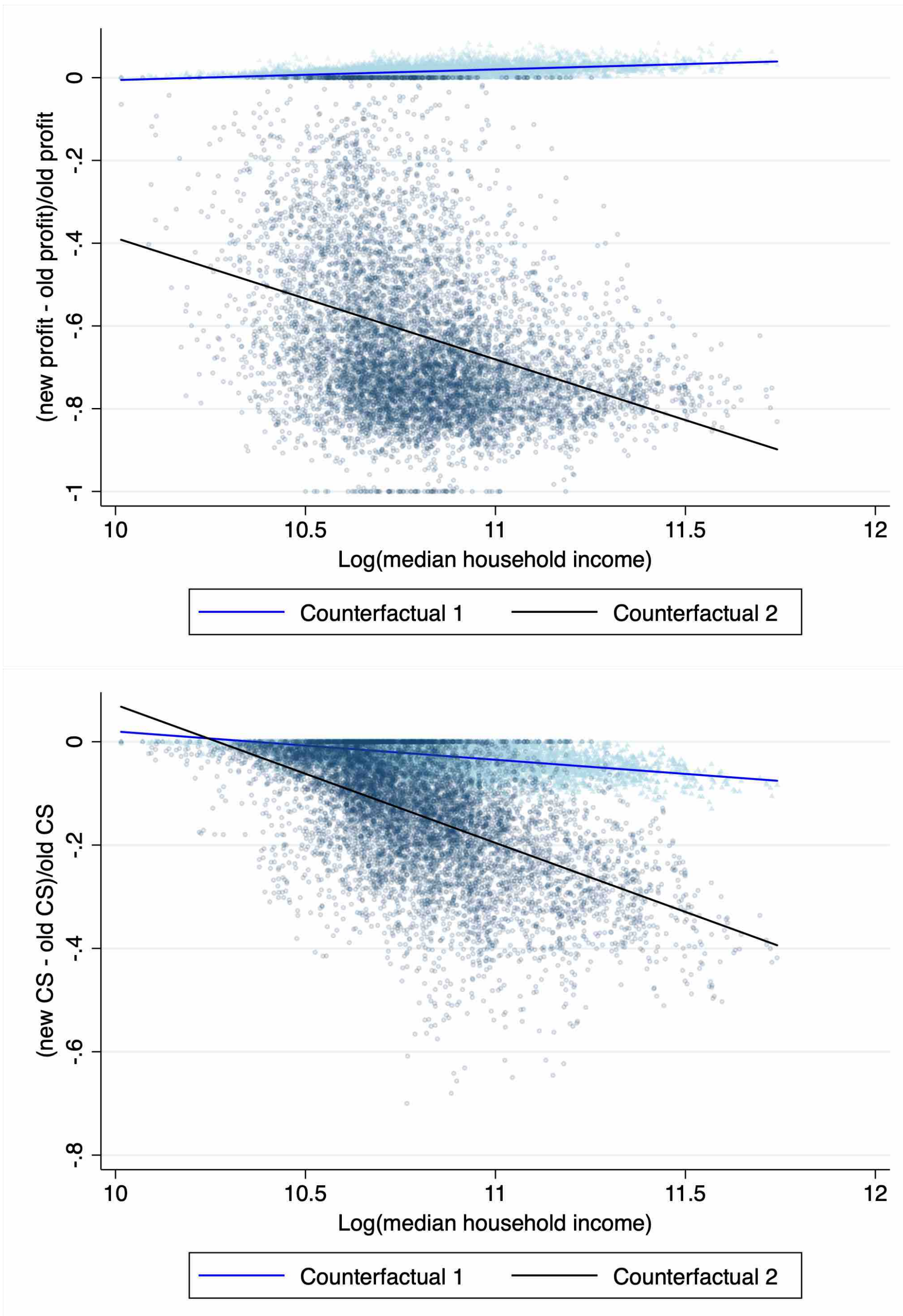


Table 1: Spatial Variations in Price Premiums

	organic p^o	non-organic p^n	Δprice $(= p^o - p^n)$
	(1)	(2)	(3)
	A. Total population		
log(population)	-0.042	-0.012	-0.032
	(0.003)	(0.001)	(0.002)
	B. Population aged 0-9		
log(population 0-9)	-0.038	-0.012	-0.028
	(0.002)	(0.001)	(0.002)
	C. Median household income		
log(income)	-0.134	0.005	-0.141
	(0.011)	(0.004)	(0.010)
	D. Fraction of college graduates		
frac.college.graduates	-0.486	-0.016	-0.488
	(0.032)	(0.011)	(0.028)

Notes: The sample includes county-level quarterly data plotted in Figures 2-4. The table reports the gradient of the fitted line in these figures. Specifically, I regress county-level price variables (p^o, p^n, or $p^o - p^n$) on county-level demographic variables. The coefficient estimates on these demographic variables are reported in the table. Standard errors are in parenthesis.

Table 2: Demand Parameter Estimates

	estimate
price	-3.030
	(1.282)
price × ln(population aged 0-9)	0.257
	(0.150)
price × ln(household median income)	-0.747
	(0.973)
price × fraction of college graduates	4.412
	(2.751)
post-recall period × recalled UPC	-0.456
	(0.036)
post-recall period × recalling firm	-0.067
	(0.032)
post-recall period × organic	-0.019
	(0.017)
#stores where product j is sold in market-year	0.005
	(0.000)
#UPCs included in product j sold in market-year	0.011
	(0.001)
#flavors of product j sold in market-year	0.007
	(0.001)
#types of product j sold in market-year	0.113
	(0.007)
fraction of dinner type among product j	-0.186
	(0.075)
fraction of vegetable type among product j	0.207
	(0.069)
fraction of fruit type among product j	0.570
	(0.090)
σ for constant	1.713
	(0.423)
σ for organic dummy	1.239
	(0.373)
ρ (nesting parameter)	0.204
	(0.037)
DMA×year×quarter	Yes
county×year	Yes
product×region×year	Yes
product×county	Yes
observations	274,412

Notes: The sample includes quarterly county-product-level data from 2011-2016. The parameters are estimated by using GMM. Robust standard errors are reported in parenthesis.

Table 3: Spatial Variations in Marginal Costs

	organic c^o	non-organic c^n	Δcost $(= c^o - c^n)$
	(1)	(2)	(3)
frac.college.graduates	-0.923	-0.640	-0.305
	(0.032)	(0.014)	(0.028)

Notes: The sample includes county-level quarterly data plotted in Figure 12. The table reports the gradient of the fitted line in the top figure. Specifically, I regress county-level cost variables (c^o, c^n, or $c^o - c^n$) on county-level fraction of college graduates. The coefficient estimates on the fraction of college graduates are reported in the table. Standard errors are in parenthesis.

Table 4: Spatial Variations in Markups

	organic μ^o	non-organic μ^n	Δmarkup $(= \mu^o - \mu^n)$
	(1)	(2)	(3)
frac.college.graduates	0.436	0.625	-0.183
	(0.004)	(0.005)	(0.003)

Notes: The sample includes county-level quarterly data plotted in Figure 12. The table reports the gradient of the fitted line in the bottom figure. Specifically, I regress county-level cost variables (μ^o, μ^n, or $\mu^o - \mu^n$) on county-level fraction of college graduates, where $\mu = p - c$. The coefficient estimates on the fraction of college graduates are reported in the table. Standard errors are in parenthesis.

Table 5: Decomposing Spatial Variations in Organic Premiums

	Δprice	Δcost	Δmarkup
	(1)	(2)	(3)
	A. Premium decline in education		
frac.college.graduates	-0.488	-0.305	-0.183
	(0.028)	(0.028)	(0.003)
	B. Premium decline in income		
log(median household income)	-0.141	-0.102	-0.040
	(0.010)	(0.010)	(0.001)

Notes: The sample includes county-level quarterly data. The table reports the gradient of the differences between organic and non-organic products, where $\Delta\text{price} = p^o - p^n$, $\Delta\text{cost} = c^o - c^n$, and $\Delta\text{markup} = \mu^o - \mu^n$. In Panel A, column 1 reports the estimate from column 3 of Panel D in Table 1. Columns 2 and 3 present the estimate from column 3 of Tables 3 and 4, respectively. Panel B reports similar estimates with respect to median household income. Standard errors are in parenthesis.

Table 6: Counterfactual Changes in Market-level Outcomes over Education

	price	cost	markup	variable profit	consumer surplus
	Δp	Δc	$\Delta \mu$	$\frac{V_o^{new}-V_o^{old}}{V_o^{old}}$	$\frac{CS^{new}-CS^{old}}{CS^{old}}$
	(1)	(2)	(3)	(4)	(5)
	A. Old equilibrium (from data)				
frac.college.grad	-0.488	-0.305	-0.183		
	(0.028)	(0.028)	(0.003)		
	B. New equilibrium from counterfactual 1				
frac.college.grad	-0.274	-0.328	0.055	0.095	-0.205
	(0.029)	(0.029)	(0.002)	(0.001)	(0.002)
	C. New equilibrium from counterfactual 2				
frac.college.grad	-0.213	-0.283	0.070	-1.062	-0.978
	(0.038)	(0.038)	(0.002)	(0.028)	(0.011)

Notes: The sample includes county-level quarterly data. Columns 1-3 report the gradient of the differences between organic and non-organic products. Panel A reports the same estimates from Panel A of Table 5. Columns 1-3 of Panel B (or C) presents similar estimates for the gradient from the new equilibrium prices, costs, and markups under the counterfactual scenario 1 where all organic firms maximize their joint profit (or the counterfactual scenario 2 where there is no organic firm in the market). Column 4 (or 5) report the gradient of the change in variable profit (or consumer surplus) with respect to the fraction of college graduates. Standard errors are in parenthesis.

Table 7: Counterfactual Changes in Market-level Outcomes over Income

	price	cost	markup	variable profit	consumer surplus
	Δp	Δc	$\Delta \mu$	$\frac{V_o^{new}-V_o^{old}}{V_o^{old}}$	$\frac{CS^{new}-CS^{old}}{CS^{old}}$
	(1)	(2)	(3)	(4)	(5)
	A. Old equilibrium (from data)				
log(income)	-0.141	-0.102	-0.040		
	(0.010)	(0.010)	(0.001)		
	B. New equilibrium from counterfactual 1				
log(income)	-0.093	-0.108	0.016	0.026	-0.055
	(0.010)	(0.010)	(0.001)	(0.000)	(0.001)
	C. New equilibrium from counterfactual 2				
log(income)	-0.069	-0.086	0.017	-0.293	-0.267
	(0.013)	(0.013)	(0.001)	(0.010)	(0.004)

Notes: The sample includes county-level quarterly data. Columns 1-3 report the gradient of the differences between organic and non-organic products. Panel A reports the same estimates from Panel B of Table 5. Columns 1-3 of Panel B (or C) presents similar estimates for the gradient from the new equilibrium prices, costs, and markups under the counterfactual scenario 1 where all organic firms maximize their joint profit (or the counterfactual scenario 2 where there is no organic firm in the market). Column 4 (or 5) report the gradient of the change in variable profit (or consumer surplus) with respect to the log of median household income. Standard errors are in parenthesis.