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The Effects of Organic Products on Conventional Products and Retailer Assortment Planning

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DEDICATION

Dedicated to my mother.

献给我的母亲.

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My sincerest gratitude goes to Dr. Yan Dong, my academic advisor and mentor for the past seven years. It was a life-changing moment when I walked into your office seven years ago, and I have never regretted choosing the academic path. You have shown me what it takes to become an academic, a caring advisor, and a good man. Without your support, this research may never see the light, and I could never be the person I am today. I would like to thank Dr. Sriram Venkataraman, whom I have the privilege to work with on multiple projects. In the process, Dr. Venkataraman has taught me various analysis methods through his detailed and thoughtful methodological guidance. As my dissertation co-chair, Dr. Venkataraman has always supported me in both research projects and the job market. I could never thank him enough for his kindness and encouragement. Thanks to Dr. Mark Ferguson, who shared valuable feedback on both my research projects and job market presentation. Thank you for everything you have done for us Ph.D. students as our department chair. Thanks to Dr. Abhijit Guha, who provided valuable feedback for my research and shared precious time for my dissertation as a committee member. I would also like to thank Dr. Jayanth Jayaram, who collaborated with me on my organic projects and has always been a great support throughout my job hunting process. Thanks to Yuqi Peng, whom I have the privilege to work with for five years. Thanks to Ruoou Li, for sharing joys and tears together. Finally, thanks to all faculties and staff in the management science department. It really feels like a home.

ABSTRACT

The rapid growth in organic products has posed a major challenge to conventional retailer assortment planning. On the one hand, conventional retailers, driven by the relatively high margins of organic products, have increased organic product offerings. On the other hand, the shelf space for conventional retailers has remained the same, with newly opened stores much smaller in sizes. Therefore, retailers need to carefully manage their conventional product assortments to harvest the benefit of offering and increasing organic product assortments. In order to manage the assortment efficiently, conventional retailers need to understand how organic products would affect their existing products, consumers, and supply chain relationships.

From the two essays that comprise this dissertation, the first essay aims to explain how organic products would affect retailers' conventional assortments, as well as how supply chain power would shift the connection between organic assortments and conventional assortment. The second essay estimates the substitution effect between organic products and conventional products, and how consumers choose between organic and conventional products while multiple other product attributes also present. Research questions proposed in the essays are answered by statistical analysis of difference-in-difference analysis, instrumental variable regressions, and structural estimations on retailer scanner panel data that contains weekly product sales over a 4-year time horizon.

Our findings suggest that a market expansion effect due to the introduction and expansion of organic products outweighs the operational costs for increasing both organic and conventional assortments. However, the supply chain power structure between retailers and manufacturers as well as retailer shelf space constraints will shift the relationship between organic and conventional assortments. We also find that consumers are more price-sensitive in organic products, and organic condition, product style, and seller attributes are all highly influential in shaping consumers' purchasing decisions.

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CHAPTER 1

OVERVIEW

In the last decade or so, the U.S. organic market has more than doubled in size (Organic Trade Association, 2018; see Figure 1.1). Driven by the relatively high margins, conventional retailers have increased organic product offerings. As a result, instead of being exclusively sold in local farms and national specialty stores such as Whole Foods Market, organic products are now available in many conventional supermarkets such as Publix, Kroger, and Target, and also in drug stores and convenience stores such as CVS Pharmacy and 7-Eleven. Despite the fast-growing trend for organic products, sales of organic food accounted for a mere 5.3% of total food sales in 2016 (Organic Trade Association, 2016), implying that 94.7% of total food sales is still attributable to conventional products. The rapid growth of organic products creates both opportunities and challenges for retailers and manufacturers. Moreover, this rapid growth also has complex effects on product assortment and supply chain operations decisions.

One of the major challenges for retailers comes from balancing the assortment between conventional and organic products given limited shelf space (Hooker & Shanahan, 2012). That is, although organic product variety has increased substantially during the past decade, retailer shelf space did not grow concomitantly. Moreover, newly opened stores are about 25 percent smaller than existing stores (McKinsey & Company, 2013). Therefore, growth in total product variety spikes operating costs and increases the possibility of stock-outs, which ultimately hurts retailers' profits (Alfaro & Corbett, 2003; Fisher & Ittner, 1999; Shockley et al., 2015; Ton & Raman, 2010). As a result, introducing or increasing organic product variety requires retailers to restructure conventional product assortments to maintain the total variety at a manageable level. This is of particular concern for stores that have tighter space constraints, such as stores located in urban areas and for convenience stores. Therefore, growth in organic product variety could possibly cannibalize conventional product variety, which ultimately hurts retailer's revenue from the conventional product segment.

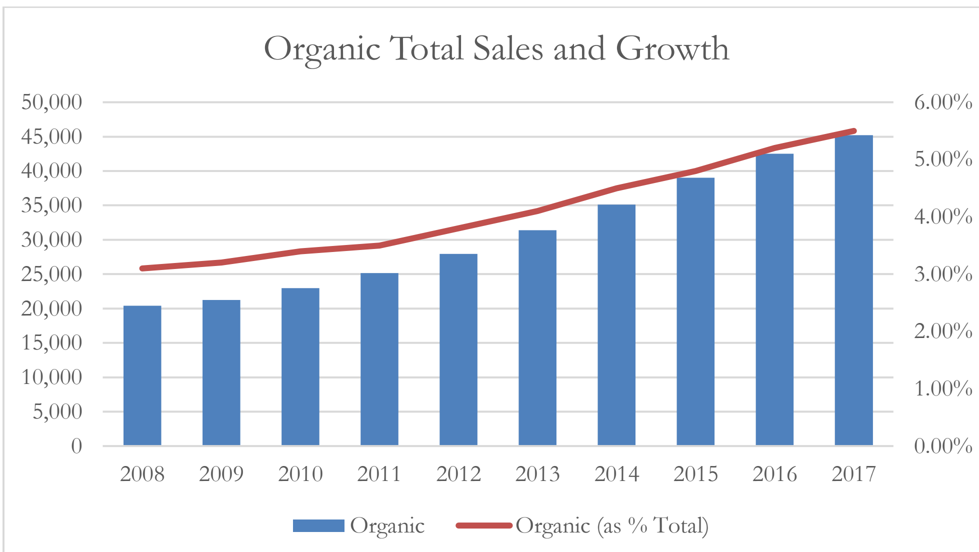

Figure 1.1: Organic Sales and Growth

Another challenge for retailers is to understand consumer substitution between organic and conventional products. Recent studies suggest that although the "hardcore" organic consumers may be less price-sensitive, the majority of organic consumers do care about organic pricing. A 2009 study by the Hartman Group found that there are three key consumer demographics: While 21% of the total consumers buy organic products exclusively, 65% of the total consumers buy both organic products and conventional products. The "occasional" organic consumers bring both opportunities and challenges to conventional supermarkets. On the one hand, carrying conventional products may reduce the loss of sales when a specific organic product is not available. On the other hand, retailers should also beware of low-margin conventional products cannibalize the sales of high-margin organic products. Therefore, it is important to understand how consumers choose between organic and conventional products and how much does conventional products cannibalize the sales of organic products. Especially for those retailers who carry both types of products.

In this dissertation, we investigate the impact of organic products on conventional products and on retailer assortment planning. In Chapter 2, we focus on how retailers would change their conventional product assortment when they first introducing organic products, as well as when they increase their organic product varieties. We use four years (2008-2011) of weekly scanner data obtained from Information Resources Inc. (IRi) and employ econometric methods to study the relationship between organic and conventional product offerings at the retail store level for the yogurt category. We find that, when stores first introduce organic products to one of their product categories, or when stores increase organic products to one of their product categories, conventional product variety in that product category also increases, *ceteris paribus*. This finding suggests that there is a market expansion effect from variety-seeking organic product customers who are drawn to stores because of the increase in organic product variety. Since the new variety-seeking consumers also tend to purchase conventional products, retail stores are encouraged to increase the variety of conventional products as well. However, we also find that this market expansion effect is constrained by store size: while larger stores can increase more conventional product variety, smaller stores can experience an overall decrease in conventional product variety. This finding confirms the presence of cannibalizing effects between organic and conventional products when capacity constraints are significant. In addition, by focusing on product assortment decision-making across the supply chain, we find that for retailers facing highly concentrated manufacturers, the positive relationship between the introduction of organic products and conventional product variety tends to be weakened. That is, the higher costs and capacity constraints associated with product variety, tends to discourage manufacturers from increasing overall product variety. We also find that, for retailers with strong private-label presence, the relationship between organic products and conventional products is reversed. That is, retailers with strong private-label presence increase private-label conventional products at the expense of national brand conventional products when they expand their organic product offerings.

In Chapter 3 of this dissertation, we focus on the relative effect of product attributes (price, brand, nutrition information, style, etc.) and seller-related attributes (store type, store size, promotion, advertising, etc.) on consumers' choices for organic products. We use four years (2008-2011) of weekly scanner data obtained from Information Resources Inc. (IRi) and employ structural estimation techniques developed in the empirical industrial organization literature to conduct our analysis (Berry 1994). Our main findings suggest that organic condition, product style, and seller attributes are all highly influential in shaping consumers' purchasing decisions. Further, the relationship between organic and conventional products is much more nuanced and context-specific than previously shown. We find organic products always have a higher own-price elasticity than conventional products, suggesting that even organic consumers are willing to pay a higher price, they are also sensitive to organic prices. We also find that the cross-price elasticities between organic products and conventional products are asymmetry. This asymmetry cross-price elasticity suggests that price change in conventional products has less effect on organic products than vice-versa, consistent with the asymmetric price competition literature (Sethuraman & Srinivasan, 2002). However, this effect is also content-specific. While in some product categories such as All-Natural yogurt and Creamy yogurt, price change in conventional products has a greater effect on organic products. This finding suggests that consumers have different preferences for different product specifications.

In Chapter 4, we conclude with a summary of findings, limitations, and future research directions.

CHAPTER 2

ORGANIC PRODUCT AND CONVENTIONAL PRODUCT ASSORTMENT: AN EMPIRICAL STUDY

ABSTRACT

The rapid growth in demand for organic products has posed a major challenge for conventional product assortment decisions in grocery stores. In this research, we address the research issue of how inducing organic product variety influences conventional product variety. Using theoretical arguments, we propose that supply chain effects, specifically, private-label presence and supplier concentration, influence this relationship. We also propose that store size can influence this key relationship. Conventional product sales account for more than 90% of total sales for grocery stores. While introducing organic products attracts new customers and increases demand, it may also cannibalize conventional product variety. Such effects have important implications to product assortment decisions in supply chains, and yet, this dilemma has received very little attention in the operations management literature. Using scanner data from retailers for yogurt purchases from 2008 to 2011, we construct panel-based econometric models to examine the relationship between organic product variety and conventional product variety. We show that when retail stores who have never sold organic yogurt in the past, first introduce organic yogurt to the store, conventional yogurt variety also increases. We also find that for retailers who expand their organic yogurt variety offerings, conventional

yogurt variety offerings also increases. Taken together, these results suggest a market expansion effect due to the introduction and expansion of organic products. However, in the presence of private-label products or with retailers facing more concentrated manufacturers, this correlation may be reversed; that is, the growth of private-label products mitigates the growth of conventional products. Also, when faced with more concentrated manufacturers, the growth of organic products lowers the growth of conventional products. Our findings suggest that when shelf space is abundant, retailers tend to increase conventional product variety along with organic product variety. However, if shelf space is limited, retailers are better off substituting conventional products with organic products.

Keywords: Organic Products, Conventional Products, Variety, Assortment Management, Supply Chains

2.1. INTRODUCTION

In the last decade or so, the U.S. organic market has more than doubled in size (Organic Trade Association, 2018; see Figure 1.1). Driven by the relatively high margins, conventional retailers have increased organic product offerings. As a result, instead of being exclusively sold in local farms and national specialty stores such as Whole Foods Market, organic products are now available in many conventional supermarkets such as Publix, Kroger, and Target, and also in drug stores and convenience stores such as CVS Pharmacy and 7-Eleven. Despite the fast-growing trend for organic products, sales of organic food accounted for a mere 5.3% of total food sales in 2016 (Organic Trade Association, 2016), implying that 94.7% of total food sales is still attributable to conventional products. The rapid growth of organic products creates both opportunities and challenges for retailers and manufacturers. Moreover, this rapid growth also has complex effects on product assortment and supply chain operations decisions.

The major challenges for retailers come from balancing the assortment between conventional and organic products given limited shelf space (Hooker & Shanahan, 2012). That is, although organic product variety has increased substantially during the past decade, retailer shelf space did not grow concomitantly. Moreover, newly opened stores are about 25 percent smaller than existing stores (McKinsey & Company, 2013). Therefore, growth in total product variety spikes operating costs and increases the possibility of stock-outs, which ultimately hurts retailers' profits (Alfaro & Corbett, 2003; Fisher & Ittner, 1999; Shockley et al., 2015; Ton & Raman, 2010). As a result, introducing or increasing organic product variety requires retailers to restructure conventional product assortments to maintain the total variety at a manageable level. This is of particular concern for stores that have tighter space constraints, such as stores located in urban areas and for convenience stores. Therefore, growth in organic product variety could possibly cannibalize conventional product variety, which ultimately hurts retailer's revenue from the conventional product segment.

The rapidly expanding demand for organic products can be attributed to the increasing number of organic product consumers. Organic product consumers tend to be health-conscious, highly educated, have higher disposable incomes and lower price sensitivities (Krystallis et al., 2006). Moreover, 75% of organic product consumers also purchase conventional products when they find conventional products to be attractive . Their variety seeking behavior could also potentially "spill-over" to purchasing other products, and the resulting market expansion effect would benefit retailers who offer both organic products and conventional products. This is especially appealing to new organic product consumers. A 2009 study by the Hartman Group reports that 21% of all consumers buy organic products exclusively, while 65% of all consumers buy both conventional and organic products (Chait, 2017), suggesting that this market expansion effect could be substantial. If this is the case, then the growth of organic products presents an opportunity for retailers to leverage growing demand from organic product customers by increasing both the variety of organic products and the variety of high-quality conventional products. Therefore, the overarching question of this paper is: Given the market expansion opportunity and assortment challenges brought about by the introduction of organic products, how do retailers manage conventional product variety while introducing or increasing organic product variety?

From a supply chain perspective, the effect of growing product variety presents different challenges for retailers and manufacturers. Increasing product variety not only increases indirect costs for both manufacturers and retailers, such as inventory carrying costs and stock-out risks, (Alfaro & Corbett, 2003; Fisher & Ittner, 1999; Ton & Raman, 2010) but also direct costs, such as increased setup times (Martin & Ishii, 1996) and change-overs (Van Ryzin & Mahajan, 1999), for manufacturers. These costs may be especially high for manufacturers who produce both organic and conventional products. Because of the strict and specialized production requirements for organic products , manufacturers could lose throughput volume and concomitant economies of scale if they introduce organic products and/or increase product variety for both organic and conventional products. Unlike retailers who could possibly benefit from increasing conventional product variety, manufacturers who try to increase both conventional and organic product offerings would most likely face higher costs and resource cannibalization issues (Roberts & McEvily, 2005). This potential misalignment between interests of retailers and manufacturers leads to our second research question: How does supply chain power, as reflected via product assortment decisions, influence the relationship between the introduction of organic products (or increasing the variety of organic products) and the variety of conventional products?

A retailer or a manufacturer could influence product assortment decisions by exerting its power in the supply chain. For retailers, sourcing from a single manufacturer weakens the retailer's control over assortment decisions and creates a source of bargaining power for the manufacturer (Newman, 1989; Porter, 2008). This is a common concern in category management, wherein retailers defer product assortment decisions within categories to a leading manufacturer (Kurtuluş & Toktay, 2004). Conversely, supplier's (manufacturer's) power over the buyer (retailer) is weakened when the retailer splits its total requirements among multiple suppliers (Burke et. al., 2007). Therefore, sourcing from a larger number of manufacturers allows retailers better control over product assortment decisions, which could then lead to a higher variety of both organic products and conventional products, thereby yielding higher total revenue.

Another common retailer practice with implications for product assortment decisions is the introduction of private-label products (Ailawadi & Keller, 2004). Private-label products are defined as store brands that are managed by retailers and are often more profitable than products of national brands (Heller, 2011; Quelch & Harding, 1996). The presence of strong private-label products could lead to higher retailer power and lower power of national brand manufacturers (Chintagunta et al., 2002; Morton &

Zettelmeyer, 2004). Therefore, retailer with strong private-label product presence could utilize its supply chain power, which then leads to a higher variety of both organic products and conventional products.

Despite the importance of product assortment decisions in supply chains, the relationship between organic product growth and conventional product assortment has not been adequately studied in the operations management literature. As the first of such efforts, this study addresses the following two important research questions: *(1) Does conventional product variety increase or decrease when organic product is introduced (or its variety increases) at the store level? (2) Does the control of assortment decisions in the supply chain affect assortments between organic and conventional products?* Specifically, in the main analysis, we first examine how conventional product variety could change when retailers first introduced organic products to the store. Second, we examine how a retailer faced with more concentrated—and therefore more powerful—manufacturers would make assortment decisions involving both organic and conventional product variety. Third, we examine how a retailer with the option of introducing private-label products would make product assortment decisions involving organic and conventional product variety. As an extension, we further broaden our research question to examine how conventional product variety would change when organic product variety increases in stores who have already sold organic products.

We use four years (2008-2011) of weekly scanner data obtained from Information Resources Inc. (IRi) and employ econometric methods to study the relationship between organic and conventional product offerings at the retail store level for the yogurt category. The major findings from this research are summarized as follows. First, we constructed a difference in differences study, using stores that started to sell organic product during our time of study and stores that has never sold organic products, to examine how conventional product variety changes when a retailer introduces organic products. We find that, when stores first introduce organic products to one of their product categories, conventional product variety in that product category also increases, ceteris paribus. This finding suggests that there is a market expansion effect from variety-seeking organic product customers who are drawn to stores because of the introduction of organic products. Since the new variety-seeking consumers also tend to purchase conventional products, retail stores are encouraged to increase the variety of conventional products as well. However, we also find that this market expansion effect is constrained by store size: while larger stores can increase more conventional product variety, smaller stores can experience an overall decrease in conventional product variety. This finding confirms the presence of cannibalizing effects between organic and conventional products when capacity constraints are significant. Second, by focusing on product assortment decision-making across the supply chain, we find that for retailers facing highly concentrated manufacturers, the positive relationship between the introduction of organic product and conventional product variety tends to be weakened. This is because such retailers have less control over the assortment decisions in the supply chain. This weakening effect, which results from the higher costs and capacity constraints associated with product variety, tends to discourage manufacturers from increasing overall product variety. Greater manufacturer control over product assortment decisions, as indicated by a more concentrated manufacturer base, allows manufacturers to counter pressures of increasing product variety away from the interests of retailers. We also find that, for retailers with strong private-label presence, the relationship between organic products and conventional products is reversed. That is, although retailers who have a strong presence of private-labels also have higher power over assortment decisions, conventional product variety in these retailers would decrease when organic product is introduced. In the extension, we further broaden our study to stores who have already been selling organic products, and examine what happens to conventional product variety when these stores increase their organic product variety. Therefore, we use all stores in our data and use instrumental variables approach to study the relationship between organic product variety and conventional product variety. In addition, we also examine how supplier concentration, private-label presence, and store size affects the relationship between organic product and conventional product variety. We find that conventional product variety is still positively correlated with organic product variety, and the same consistent results holds true in the presence of higher supplier concentration and private-label presence. This finding suggests that the market expansion effect is not limited to stores that first introduced organic products, but also holds for stores that have already offered organic products. We further find that retailers with strong private-label presence increase private-label conventional products at the expense of national brand conventional products when they expand their organic product offerings. In addition, after controlling for market demand and population density, we find larger stores tends to increase more conventional product variety.

Our research contributes to the operations management literature as follows. First, we distinguish how increasing organic product variety is different from a price discrimination strategy which is based on consumers' willingness to pay for quality

(Mussa & Rosen, 1978; Moorthy, 1984; Horsky & Nelson, 1992). However, while price discrimination strategy may not increase total demand (Quelch & Kenny, 1994), increasing organic product offerings increases total demand by attracting new, variety seeking organic consumers. Similarly, while price discrimination strategy is prone to the cannibalization problems (Randall et al., 1998), retailers actually benefit from the fact that organic consumers would also purchase conventional products. Therefore, we contribute to the literature by empirically investigating the impact of organic product variety on conventional products as an assortment outcome. Second, we contribute to the literature by establishing the role of supply chains in assortment decisions involving organic products. Managing organic products in supply chains poses a significant challenge to making product assortment decisions because the benefits and costs associated with organic product offerings are not congruent among supply chain members. We show that assortment decisions are associated with supply chain governance and control and that retailers benefit from market expansion and, therefore, play a leading role in the movement towards organic product introduction. We demonstrate that retailers with a larger percentage of private-label products, or those sourcing from a larger group of manufacturers, tend to have more control over the assortment decisions and tend to take advantage of greater organic product variety. Taken together, these findings suggest that the growth of organic products is demand-driven and that there is a variety-seeking organic customer base that spills over to the demand for conventional products, thereby expanding the conventional product market. However, this effect may be mitigated by small store size, which is indicative of capacity constraints. Our findings also highlight the fact that power distribution in the manufacturer-supplier supply chain could affect the growth in conventional product variety.

The remainder of this paper is organized as follows. Section 2.2 provides a review of the organic product and product assortment literature. Data, including dependent variable, independent variables, and control variables, are described in Section 2.3, and the difference-in-differences model is described in Section 2.4. The results are presented in Section 2.5. We present model extensions and discuss results and alternative explanations in Section 2.6. Finally, we provide the theoretical and managerial implications of this research and conclude in Section 2.7.

2.2. Literature Review

In this section, we review the literature from three related streams of research: organic products, product assortments, and supply chain governance. Our review is grouped according to demand-side issues and supply-side issues as it pertains to our research questions. We first discuss the impact of organic products on the food supply chain. We then turn to product assortment decisions that have implications for retailers, manufacturers, and customers. Finally, we review the role of supply chain governance issues, such as power, in product assortment decisions.

2.2.1 Impact of Organic Products on Food Supply Chains

On the demand side, consumer demand for organic products has grown by double-digits almost every year since the 1990s. Organic product sales have increased from $3.6 billion in 1997 to $47 billion in 2016 (Organic Trade Association, 2016). Consumers value organic food because it is seen as being healthier, more nutritious, better tasting, and safer because no chemicals are used in its production (Bauer et al., 2013). They buy organic produce according to the "dirty dozen and clean fifteen" standards, which identify groceries with the most pesticide residue and those with the least contamination (Pou, 2010). Organic farming is also perceived to be "gentler" on the environment and is therefore seen as being more socially responsible (Fotopoulos & Krystallis, 2002; Larue et al., 2004; Wier & Calverly, 2002). Consumers of organic products tend to have higher education, namely a graduate degree (Govindasamy et al., 2017; Grossman, 1972; Lockie, 2002; Schifferstein & Ophuist, 1998) and income levels above $75,000 (Kriwy & Mecking, 2012; Zhang et al., 2008). Importantly, this growing segment of consumers does not exclusively buy organic products. A 2009 study by the Hartman Group found that, while 21% of consumers buy organic only, 65% of consumers buy both conventional and organic products (Chait, 2017). Evidence shows that organic customers also purchase conventional products if they find them attractive, particularly when the prices of organic products are too high or when the supply of organic products is limited (Hudson, 2012).

On the supply side, organic products are expensive to grow and produce throughout the supply chain partly due to stringent standards (Dumas, 2015). The United States Department of Agriculture (USDA) imposes specific requirements that must be verified by an accredited third-party certifying agent before products can be labeled as "organic." For instance, the use of synthetic fertilizers, pesticides, herbicides, irradiation, sewage sludge, hormones, antibiotics, and genetic engineering is strictly prohibited (USDA, 2019). Other reasons for the higher cost of organic food include farming practices that usually require high labor content and the segregation of organic ingredients from conventional ones. All of these factors contribute to higher prices for organic products compared to their conventional product counterparts (see Figure 2.1). At the same time, organic products enjoy higher gross margins, ranging from 30% to 50%, compared to margins of conventional products, which range from 20% to 25% (Bezawada & Pauwels, 2013; Oberholtzer et al., 2006; Roheim & D'Silva, 2009). In sum, the growing organic product offerings provide opportunities for market expansion but pose serious challenges in product assortment decisions and cost efficiencies in the supply chain. To the best of our knowledge, no prior research in the literature of operations management has addressed these opportunities and challenges.

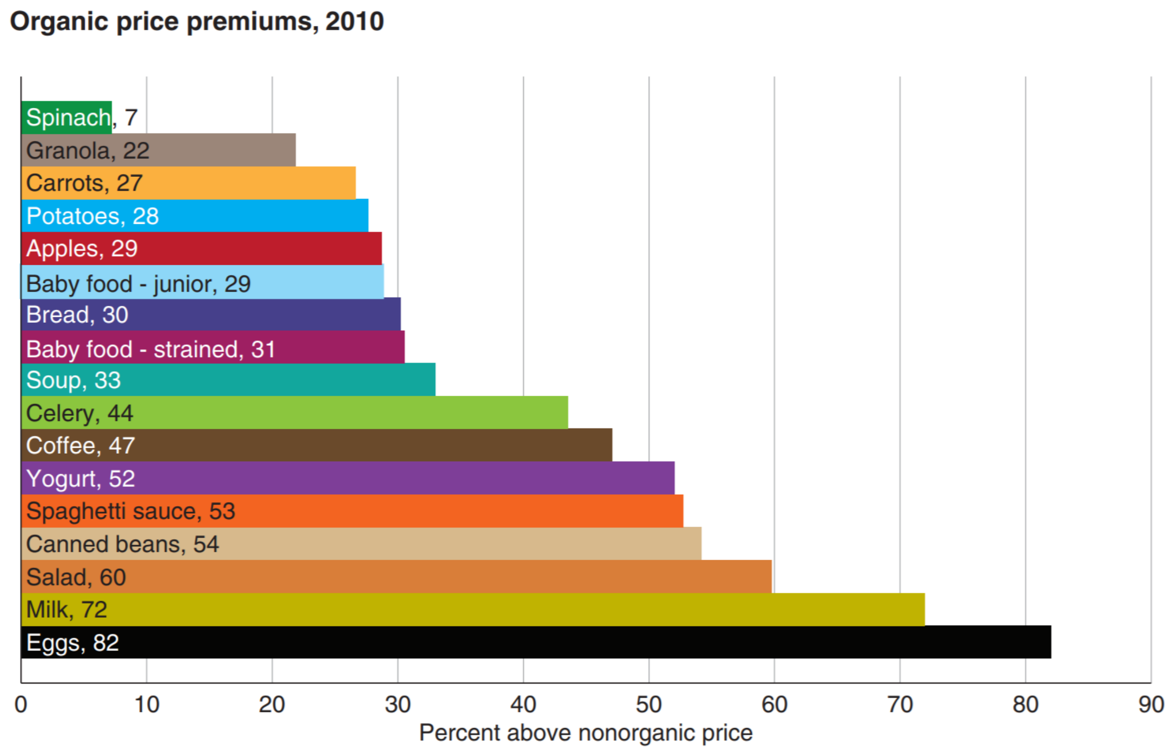

Figure 2.1: Organic Food Price Versus Conventional Food Price

Source: USDA, Economic Research Service estimates from Nielsen Homescan data (2010)

2.2.2. Price Discrimination Strategy and Assortment

Introducing or increasing product variety for organic products is similar to price discrimination strategy, where organic products are introduced in the same product category but with a different price and quality balance (Pitta & Prevel Katsanis, 1995). However, the growth of organic product variety affects assortment decisions in a way that is quite different from traditional price discrimination strategy. In this section, we will first focus on assortment studies from the retailers' and manufacturers' perspectives, and discuss why it is different from price discrimination strategy.

From a retailer's perspective, price discrimination strategy generally refers to increasing product variety, which stimulates sales by segmenting customers and attracting variety-seeking shoppers (Bayus & Putsis, 1999; Ton & Raman, 2010; Xia & Rajagopalan, 2009). Similarly, there are also challenges to carrying a higher variety of products. High variety drives lower inventory levels of individual items, which reduces the items' visibility on shelves, increases the risk of stock-outs, and imposes high restocking costs due to the need for frequent replenishment (see Mantrala et al., 2009 for an extensive review). High variety also drives up operations complexity, which also leads to higher costs (Shockley et al., 2015). In addition, high variety is also constrained by the ultimate retailer resources----the shelf space available in stores (Corstjens & Doyle, 1981). Last but not the least, high variety would lead to cannibalization; lower end products would cannibalize the sales of higher end products, leading to profit loss (Parlaktürk, 2012).

Given the tradeoff between profit generation and cost efficiency, prior research reports mixed findings of both a positive relationship between assortment depth and category sales in some cases (Borle et al., 2005; Van Ryzin & Mahajan, 1999) as well as a negative relationship in other cases (Boatwright & Nunes, 2001; Broniarczyk et al., 1998; Dreze et al., 1994). However, there are several aspects that sets organic products apart from traditional price discrimination strategy. Firstly, organic products attract new organic consumers to retail stores that previously did not carry organic products; this new customer base increases demand. We refer to such effect as "market expansion." Therefore, price discrimination strategy is favorable to retailers because offering new organic products (or increasing variety of organic products) would actually increase the total category demand. Second, among these new organic consumers, the majority are also willing to buy conventional products. Imagine a scenario where a retail store only carries conventional yogurt products such as Yoplait and Dannon Original. When the store starts to carry Stonyfield Organic yogurt, it attracts new organic consumers, who had never shopped at the store. In addition, the majority of these organic consumers would also purchase high-end conventional yogurts such as Chobani Greek yogurt, which the store had never carried before. It would be more beneficial for this retailer to simultaneously introduce both the Stonyfield Organic yogurt and the Chobani Greek yogurt to better serve the new organic consumers. Therefore, due to the fact that the majority of organic consumers also purchases high-end conventional products, the cannibalization effect from the lower-end products (Yoplait and Dannon Original) to higher-end products (Stonyfield and Chobani) are less of a concern. Rather, retailers could introduce more high-quality conventional products to attract organic consumers when organic products are out of stock. Taken together, without the concern of steady category demand or cannibalization issues, we believe that the "market expansion" effect of organic products would be more pronounced than the cost associated with increasing overall product variety. Therefore, increasing conventional product variety along with offering organic products will be more beneficial for most retailers.

From a manufacturer's perspective, the introduction of line extensions by manufacturing firms is motivated by a number of factors including, targeting different customer segments and/or satisfying the customers' desire for 'something different', matching a competitor's successful line extension, increasing the firm's share of retail shelf space allocated to the category, and utilizing excess manufacturing capacity (Quelch & Kenny, 1994). However, the pitfalls of product line extension are also significant. Over-segmentation would cannibalize company resource and confuse consumers; increasing number of suppliers would diminish manufacturing control and power; and ultimately, product lines would cannibalize each other (Quelch & Kenny, 1994; Roberts & McEvily, 2005).

More specifically, increase in product variety could lead to higher cost in the supply chain. This is because increasing total variety is not only associated with indirect costs, such as inventory stock-out costs (Alfaro & Corbett, 2003; Fisher & Ittner, 1999; Ton & Raman, 2010), but also with direct costs, such as increased setup times (Martin & Ishii, 1996) and change-over costs (Van Ryzin & Mahajan, 1999). Therefore, simply increasing variety does not guarantee an increase in long-term profits and can, in fact, reduce cost competitiveness (Ramdas & Sawhney, 2001). Using a rational approach, firms should strive to balance the revenue and cost impact of variety decisions (Lancaster, 1990) to maximize long-term profits. MacDuffie, Sethuraman, and Fisher (1996) identify three types of variety—model-mix variety, options variety, and parts variety—and they find that increasing parts variety significantly reduces productivity. For consumer product manufacturers, increasing organic product variety significantly increases parts variety because the raw materials of organic products must also be organic (e.g., organic milk, fruits, and vegetables), and therefore, they are different from materials used for conventional products (e.g., conventional milk, fruits, and vegetables). These raw material differences further complicate operations and increase costs by undermining the delayed variation strategy, wherein manufacturers benefit from the reduction in buffer inventories via risk pooling and increased flexibility (Lee & Tang, 1997). In addition to the costs of strategic changes, manufacturers also face higher costs as organic product variety increases because of the limited supply of organic materials and stricter regulations for production and sourcing processes of organic products (Klonsky, 2012). Taken together, increasing organic variety has much more significant cost implications to manufacturers than to retailers. The misalignment of interest between retailers and manufacturers is significant, and therefore, in the next section, we review supply chain governance literature and investigate how supply chain power influences the assortment outcomes on the retailer's side.

2.2.3. Assortment Decisions in Supply Chains

As we can see from the previous subsection, the effects of organic product assortment on retailers and manufacturers are different, with retailers largely benefiting from market expansion, and manufacturers incurring much of the costs. This divergence of interests and incentives across the supply chain highlights the need for considering the role of supply chain power structure on product assortment decision making. More specifically, product assortment decisions in supply chains are often controlled by parties with power, which can be manifested by a higher concentration of retailers or of manufacturers. For instance, we expect retailers facing highly concentrated manufacturers to carry a different product assortment (which benefits manufacturers) than that from retailers facing less concentrated manufacturers.

Much of the long-established debate concerning retailer-manufacturer relationships has focused on the issue of power and the balance of power within these relationships (El-Ansary & Stern, 1972; French et al., 1959; Gaski, 1984; Hunt & Nevin, 1974; Lusch & Brown, 1982). Central to this debate is the issue of dependency, whether real or perceived. Steiner (1984) argues that the relative power of manufacturers and their retailers is governed by whether shoppers are inclined towards switching stores within brands or brands within stores. In the case of the former, manufacturers will dominate the channel, while in the case of the latter, retailers will hold sway. Next, we elaborate on the two key factors that contribute to the power relationships between the retailer and manufacturer.

First, a concentrated manufacturer base means that retailers will find it difficult to find alternative suppliers for products demanded by their end customers, which gives these manufacturers more power in the relationship. For example, because the soft drink industry is highly concentrated (dominated by Coca-Cola, PepsiCo, and Dr. Pepper), no major retailer can delist Coco-Cola and its high-performing brands. If a retailer were to do so, it might lose a big portion of its customer base. A concentrated group of manufacturers may create a consolidated force that influences product assortment decisions, which are, in turn, based on profit margins and product availability (Steiner, 1993). For instance, powerful manufacturers may strategically choose to produce less differentiated products, which reduces product variety and their own costs (Inderst & Shaffer, 2007). Therefore, when manufacturers are more concentrated, they have more power and control over product assortment decisions. Thus, in this case, lower conventional product variety is expected such that the combined product variety (organic and conventional) does not increase excessive direct costs. On the contrary, when manufacturers are more diffused, retailers have more power and control over product assortment decisions, and we would expect higher conventional product variety in stores so that retailers are able to benefit from the market expansion effect.

Second, power in the supply chain has largely shifted toward retailers over the years, aided by the proliferation of private-label products . Private-label products are store brands owned by retailers. This ownership often results in higher margins that provide incentives for retailers to grow their market share of private-label products via low wholesale and retail prices (Bontems et al., 1999; Meza & Sudhir, 2010). In addition, private-label products enhance store brands with better product and service quality, customer loyalty, store differentiation, and store profitability (Ailawadi et al., 2008; Corstjens & Lal, 2000; Martos-Partal & González-Benito, 2011). In sum, extensive private-label coverage yields retailers more power and control over product assortment decisions (Dunne & Narasimhan, 1999; Quelch & Harding, 1996). Narasimhan and Wilcox (1998) argue that retailers introduce private-labels in a category not only to gain profits directly from the private-label but also to use private-labels as a strategic weapon to elicit concessions from national brand manufacturers. More importantly, Meza and Sudhir (2010) found that retailers not only gain power from private-labels, but also strategically help private-labels gain market share by setting the corresponding national brand product price higher than its optimal price. Similarly, research has also found that retailers would protect their private-label products by reducing the presence of the competing manufacturers' products in their assortment (Alan et al., 2017). Moreover, lower quality national brand products are less profitable when competing with private-label products (Alan et al., 2019). This raises a contradictory effect in our research context wherein retailers have greater power and control on product assortment decisions, and yet conventional product variety also decreases. Retailers with strong private-label product lines would utilize their private-label products to further increase their supply chain power. Therefore, such retailers could increase private-label product variety (organic and conventional) to attract organic product consumers, but at the same time decrease branded conventional product variety to maintain both operational efficiencies and enhanced supply chain power. Therefore, the overall effect of introducing organic products (or increasing organic product variety) on conventional product variety at the store level may be negative.

In summary, the rapid growth of organic products has challenged product assortment decision making in supply chains. This is particularly true for conventional products that remain the dominant source of revenue for most retailers. Because prior research that links assortment of organic products and conventional products is limited, we empirically examine the relationship between organic products and conventional product variety and test how this relationship is affected by supply chain power and the ensuing product assortment decisions. More specifically, we examine how manufacturer concentration and the presence of private-label products affect the relationship between organic product variety and conventional product variety.

2.3. Data and Measures

We first describe our data source and sample size in Section 2.3.1. Since we measure both the introduction of organic products (main analysis) and the increase of organic products (extension), we describe our full data sample in section 2.3.1.1, and the data sample used for difference-in-differences analysis in section 2.3.1.2. We then describe the dependent, independent, and control variables used in our analyses in Section 2.3.2.

2.3.1.1 Full Sample Data

We use four years of proprietary scanner data (2008-2011) from IRi, which reports data for grocery chains and drug stores in 50 markets in the U.S. (except Alaska and Hawaii). The raw data contains three files that separately report: 1) weekly Stock Keeping Unit (SKU) sales and unit price, 2) SKU attributes (e.g., product type, organic status, and product size), and 3) store information (location, chain affiliates, market, and store's annual sales). An SKU is defined as a unique combination of brand, flavor, weight, container material, container size, and pack size. We first use the Universal Product Code (UPC) number to identify each SKU and then combine the SKU sales data with the SKU attributes data. We then use the store ID from both the SKU sales data and store information data to arrive at our final sample. We use data pertaining to the yogurt category for two main reasons. First, we observe weekly sales data only and not the actual shelf display data. Fast-moving items such as yogurts have a comparably shorter shelf life. Therefore, for such items, the number of SKUs sold in each week is a good approximation of the number of SKUs on the shelf. Second, the assortment of yogurts has changed dramatically over the years. For example, the total number of varieties of yogurt in the US market soared 32% from 4,581 in 2008 to 6,053 in 2011. In comparison, the organic SKU category increased 30%, from 256 SKUs (in 2008) to 331 SKUs (in 2011). The yogurt category in the raw data has 7,112 SKUs in total, including discontinued SKUs and yogurt by-products, such as almond yogurt, buffalo milk yogurt, yogurt smoothies, and kefir. We dropped all yogurt by-products in our study to focus on the main yogurt category products. Figure 2.2 shows the time-series data of the ratio of total organic yogurt sales revenue to conventional yogurt sales revenue. As can be gleaned from this figure, the ratio of total organic yogurt sales revenue to conventional yogurt sales revenue in year 2008 was 7.73% (32 million dollars compared to 414 million dollars, respectively). In 2009, the ratio increased slightly to 7.77% (34.1 million dollars compared to 439 million dollars, respectively). However, since 2009 this ratio shows a decreasing trend. In particular, in 2010, the ratio decreased to 7.68% (33.7 million dollars in organic sales compared to 439 million dollars in conventional sales), and in 2011, this ratio decreased to 6.61% (28.9 million dollars in organic sales compared to 437 million dollars in conventional sales). The decline in market share of organic yogurt after 2010 may reflect growing nonorganic sales of Greek-style yogurt and yogurt drinks, products that were not readily available in organic forms (USDA, 2017). Our final sample is an unbalanced panel dataset that contains 208 weeks of data for 1,896 stores in 50 markets. Two kinds of stores are included in our dataset: grocery stores and drug/convenience stores. There are 1,561 grocery stores and 335 drug/convenience stores in our final sample. Our dataset does not contain wholesale clubs such as Costco and Sam’s Club. Across all the stores, there are 6,053 yogurt SKUs, including 242 brands produced by 88 manufacturers (including private-labels).

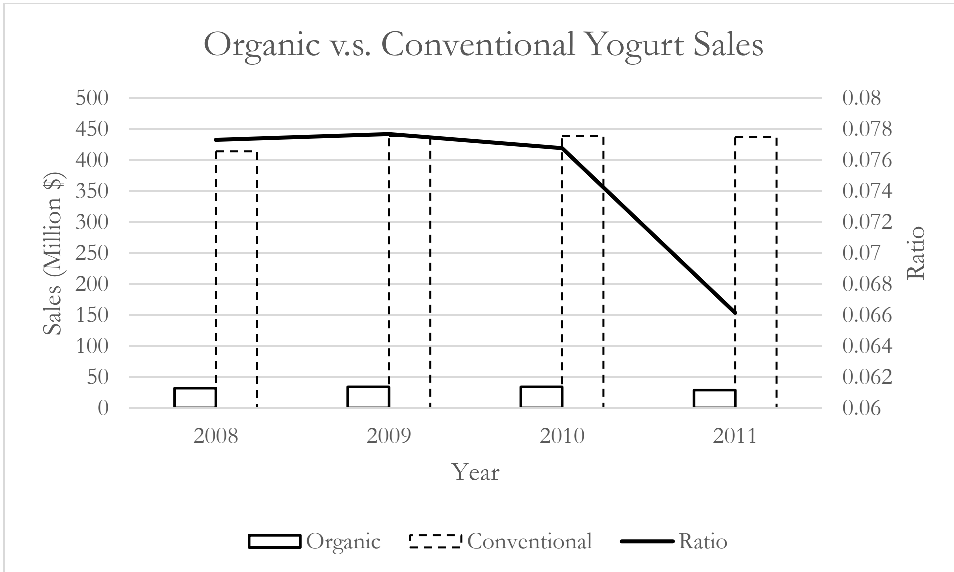

Figure 2.2: Data Description: Organic versus Conventional Yogurt Sales

2.3.1.2 DIFFERENCE-IN-DIFFERENCES DATA

We further identify stores that has never sold organic products during the 4-year time span and stores that started to sell organic products during the 4-year time span. Among the 1,896 stores in the full sample, 113 stores began selling organic yogurt at some point during the study period (treatment), and 431 stores have never sold any organic product during the 3-year time span (control). By observing the store annual revenue, we find that the treatment stores are heavily skewed towards the "large store" side, therefore, for the quality of the propensity score matching, we further trimmed down our sample by dropping the treatment stores that fall in the top 10% annual revenue, and the bottom 10% annual revenue. Our final sample arrives at 81 treatment stores and 431 control stores. In addition, out of the 81 stores that introduced organic products during our observed time span, 12 stores introduced organic products from a new supplier that was previously not in the stores' supplier list whereas the remaining 69 stores introduced organic product from an existing supplier.

2.3.2.1. Dependent Variables

$ConVar_{it}$ represents the number of conventional SKUs in store i at week t. The number of SKUs is a well-accepted measure of product variety in the extant literature (Alfaro & Corbett, 2003; Borle et al., 2005; Fisher & Ittner, 1999; Wan et al., 2012). SKU is a unique identifier of a product; any changes in a product (i.e., manufacturer, brand, flavor, size, or packaging) would result in a new SKU. We specifically grouped and calculated our product variety variables based on the requirements of each of our research questions. For example, in order to test the effects on conventional product variety, we calculated the number of SKUs of conventional yogurt sold in store i at week t. As explained above, the number of SKUs sold is a good proxy for the number of SKUs carried in the store because yogurts are fast-moving items that have a relatively shorter shelf life.

2.3.2.2. Main Independent Variables

$Treat_i$ represents the indicator for stores that began to sell organic yogurts during our time span. It is coded as 1 for all stores that launched organic yogurt products within our observed time frame and 0 for all stores that never sold organic yogurt products within our observed time frame.

$After_{it}$ is 1 for all weeks after organic yogurt is introduced for both the treatment group and its constructed control group, and 0 for all weeks before organic yogurt is introduced for both the treatment group and its constructed control group. Our focal independent variable therefore is the interaction between the $Treat_i$ and $After_{it}$. Using difference-in-differences analysis, we compare the change in average conventional product variety in stores that do not introduce organic products and stores that introduce organic products.

$PriLabel_{it}$ represents the ratio of private-label SKUs to the total number of SKUs in store i at week t. To test the effect of private-label presence for a store, we measured the proportion of shelf space occupied by private-label yogurts in a store. Prior studies have considered private-label revenue share as a proxy for the proportion of shelf space occupied by private-label products in a store (Ailawadi et al., 2008; Corstjens & Lal, 2000). However, this may not be an appropriate measure in our context because large revenue could be generated by a few product assortments. In order to account for the shelf space taken up by private-label products, we created the private-label product variety ratio, calculated as the ratio of the number of private-label SKUs to the total variety. We used private-label variety ratio instead of the number of SKUs of private-label products because this ratio better represents the significance of private-label products at the store level. This measure is similar to the one used by Gómez Suárez (2005), who defined the percentage of space occupied by private-label as follows:

$$PriLabel_{it} = \frac{Number\ of\ store\ brand\ SKUs\ in\ store\ i\ at\ week\ t}{Number\ of\ total\ SKUs\ in\ store\ i\ at\ week\ t}$$

HHI_{it} represents the manufacturer concentration in store i in week t of year T. To test the effect of manufacturer concentration, we calculated the store level Herfindahl-Hirschman index (HHI) for the store's suppliers. The HHI is the most frequently used measure of market concentration to study market structure and firm performance (Cotterill, 1986). In our case, a higher HHI implies a more concentrated base of manufacturers for the store. In particular, we first calculated the ratio of annual revenue generated by each yogurt manufacturer for each retail chain and then calculated the sum of the squared term of each manufacturer's revenue ratio to the chain to compute the HHI. We use retail chains instead of single stores because product assortment decisions are mostly chain-level decisions, and store branches do not have the power to negotiate with yogurt manufacturers in terms of their product assortment offerings. We used annual revenue ratio instead of weekly ratio because revenue ratio may change dramatically on a weekly basis depending on store promotions, advertisements, and new product launches. In addition, grocery chains do not tend to negotiate with the manufacturers and change their product assortments on a weekly basis. We believe that using annual revenue ratio best represents the market concentration of manufacturers in a retail chain.

$$HHI_{it} = \sum_{j} \left(\frac{Revenue\ from\ manufacturer\ j\ in\ year\ T}{Total\ revenue\ in\ year\ T}\right)^2$$

2.3.2.3. CONTROL VARIABLES

We control for other time-varying product and store characteristics that could correlate with our dependent variable.

$MeanPackage_{it}$ represents the average size of products in pints in store i at week t. This variable primarily measures the average size of a product's package. We calculated the average size of all yogurt SKUs to come up with this measure. Larger stores typically have higher average product size, and they carry more product variety than smaller stores (e.g., big-box retailers compared to convenience stores). Therefore, we expect $MeanPackage_{it}$ to be positively correlated with our dependent variable ($ConVar_{it}$).

$AdShare_{it}$ measures the percentage of yogurt that was on store advertisements (e.g., posters) in store i at week t. The display of the products that are advertised may be different from the display of products that are not advertised. Stores may assign additional space to the displayed products to catch the eyes of consumers. This could lead to a higher number of SKUs displayed in the original shelf space since the advertised products might be moved to the advertising shelf. Therefore, more unique SKUs may be sold (or stocked) in a store *i* with higher $AdShare_{it}$, in week *t*.

$$AdShare_{it} = \frac{Number\ of\ SKUs\ on\ advertisement\ in\ store\ i\ at\ week\ t}{Number\ of\ total\ SKUs\ in\ store\ i\ at\ week\ t}$$

$DiscountShare_{it}$ measures the percentage of yogurt that was on sale in store *i* at week *t*. We use this variable to control for promotion-related effects. Promotions may affect the total variety of the product assortment because promotions may attract more customers (Lam et al., 2001). Stores may adjust their product assortment decisions based on customer traffic. Thus, stores with higher $DiscountShare_{it}$ may have higher variety of products.

$$DiscountShare_{it} = \frac{Number\ of\ SKUs\ on\ discount\ in\ store\ i\ at\ week\ t}{Number\ of\ total\ SKUs\ in\ store\ i\ at\ week\ t}$$

$TotalQuantity_{it}$ measures the store $_i$'s total yogurt sale at week $_t$. This variable could measure two different features of a retailer. First, larger stores will have higher total quantity of products sold. Second, this variable could represent the speed of sales. If a store's products move quickly, the store may have higher demand. Thus, keeping more SKUs may help the store to achieve a higher fill rate. Therefore, we expect $TotalQuantity_{it}$ to be positively correlated with conventional product variety.

$StoRev_{it}$ is the annual revenue of store *i* in all product categories. Since we only have yearly revenue data, store revenue for a specific store remains the same for all weeks in a given year. In our study, this variable serves as another proxy for store size. Therefore, we expect $StoRev_{it}$ to be positively correlated with conventional product variety.

OM_{it}, CM_{it}, and MM_{it}, respectively, measure the number of organic suppliers, conventional suppliers, and suppliers that offer both organic and conventional products in the market where store i operates. These three variables capture the market level information for a store.

Table 2.1 gives a detailed description and summary statistics for the important variables in this study. Correlations of all the important variables of this study are given in Table 2.2.

2.4. Econometric Models and Estimation Strategy

As discussed earlier, in this research, we assess (1) the impact of introducing organic products on conventional product variety; and (2) the effect of supply chain power structure on the relationship between introducing organic products and the conventional product variety. To make an accurate estimation, we need to benchmark the changes in conventional product variety of a treatment group against a control group and employ difference-in-differences analysis. To estimate the impact of introducing organic products, we compare conventional variety change between stores that introduced organic products to those that never introduced organic products.

In an ideal scenario, stores should be randomly assigned to the treatment group (introducing organic products) or the control group (not introducing organic products), and the treatment should start at the same time for all treatment groups in the treatment group. However, in our research context, stores choose to introduce organic products, and they choose to do so at different times. Therefore, we face two methodological issues: self-selection of treatment group and sliding window for the treatment.

The self-selection of treatment group may bias the estimation of treatment effect because stores may decide to introduce organic products based on other unobserved factors that relate to conventional product variety. For example, stores that want to attract more consumers may decide to introduce organic products, whereas stores that already perform well may decide not to introduce organic products. In other words, the average attributes of stores that introduced organic products may be systematically different from those who did not introduce organic products. This difference may bias the effect of treatment if we simply consider the stores that introduced organic products as treatment group and others as control group. To resolve this potential issue, we apply the propensity score matching method to construct a control group that is comparable to the treatment group in terms of the likelihood to introduce organic products before the occurrence of the actual treatment (Heckman et al. 1997, Rosenbaum and Rubin 1983). Because we have a relatively small number of treated stores (stores that introduced organic products) compared with the large pool of candidates (stores that never introduced organic products) for the control group, we specify a 5 nearest-neighbor matching. This procedure matches each store in the treatment group to 5 stores in the control group based on store characteristics that may influence the decision of a store to introduce organic products. The matching ensures that the treatment and control groups are co mparable before the treatment occurred. The variables we use to match the two groups of retail stores are average package size of the store (MeanPackage), advertisement share (AdShare), discount share (DiscountShare), and weekly sales quantity (TotalQuantity).

If the all stores in the treatment group launch organic products at the same time, we could easily separate the post-treatment periods from the pre-treatment periods and compare the average conventional variety changes of the treatment and control groups. The sliding window of the occurrence of treatment complicates the definition of post-treatment periods for the control group. For example, store A introduced organic products in the 10th week of 2008, whereas store B introduced organic products in the 20th week of 2009. It is then not straightforward to define which weeks should be the post-treatment periods for stores in the control group. To resolve this issue, we define the post-treatment period of each treated store as the weeks after it introduced organic products, and define the post-treatment period of each control store the same way as that of the treated store to which the control store is matched (Rosenbaum & Rubin 1985). For example, if stores C and D are selected to be the matched controls of stores A and B, respectively, then the post-treatment period of store C is the 10th week of 2008 and subsequent weeks, and the post-treatment period of store D is the 20th week of 2009 and subsequent weeks.

2.4.1. PROPENSITY SCORE MATCHING

To assess the effect of introducing organic products, we apply a propensity score matching model to obtain a control group that could serve as a good counterfactual, against which we benchmark the conventional product variety change in stores after introducing organic products. In this model, we use a Probit regression, where the introduction of organic products is coded as a binary dependent variable. The covariates include factors that potentially influence the decision to introduce organic products (the matching variables listed above). Because a store could introduce organic products during any week in the 208 weeks of our data, we treat each time period as discrete (Sianesi 2004) and perform the propensity score matching in each given week (i.e., 208 times). More specifically, in each week t, we use the average values of covariates from week 1 to week t-1 as independent variables in the matching model (Austin 2011). We specify model (2.1) for each store *i* at week *t*:

$$\Pr(Treat_{it} = 1|Z_{it}) = \phi(Z_{it}\beta), \forall t = 1, 2, \dots, 208; \quad where \;\; Z_{it} = \frac{1}{t-1}\sum_{k=1}^{t-1} X_{ik} \tag{2.1}$$

where X_{ik} is a vector of all matching variables including *MeanPackage*, *AdShare*, *DiscountShare*, and *TotalQuantity* for store *i* at week *t*, and Z_{it} is the average of the above variables from week 1 to week *t-1*. Since we will use *PriLabel*, *HHI*, and *StoRev* as indicators of supply chain power and shelf space constraints in our main analysis, we do not include them in the propensity score matching to avoid multicollinearity issues in our regression models. Further, we use the nearest-neighbor matching algorithm to select five control firms that share the closest propensity scores with each treated firm with replacement. To ensure that the average conventional product variety change of the five control stores serves as an appropriate counterfactual for that of the corresponding treated store, we weigh each treated observation by 1 and each control store by sampled frequency divided by 5 (Hirano et al. 2003, Stuart 2010). For example, if a control store was assigned to one treated store, its weight is one-fifth; if a control store was assigned to two treated stores, its weight is two-fifths. We then multiply the dependent variable and covariates by the assigned weight (Winship & Radbill 1994, Wooldridge 2010) and use these adjusted values in the difference-in-differences regression.

Table 2.1: Variable Description

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
ConVar	Conventional product variety	66281	52.5378	63.52492	1	347
Treat	Stores that introduced organic products	66281	0.22899	0.420189	0	1
After	Treated time for both treatment and control group	66281	0.62393	0.484400	0	1
PriLabel	Ratio of private-label yogurt SKU to total yogurt SKU	66281	0.08825	0.124820	0	1
HHI	Chain HHI Index	66281	8.19546	0.282526	7.27077	9.21034
StoRev	The store total revenue of the year, a proxy of store size	66281	24.0418	16.92419	0.11	146.241
MeanPackage	The average package size of yogurt	66281	0.60617	0.212650	0.25	1.313043
DiscountShare	The percentage of yogurt sold was discounted	66281	0.18127	0.247328	0	1
AdShare	The percentage of yogurt sold was advertised	66281	0.01962	0.068802	0	0.861111
TotalQuantity	The number of yogurt sold at store	66281	684.819	1252.966	1	14380
OM	Number of organic product suppliers on the market	66281	4.22700	1.67215	0	9
CM	Number of conventional product suppliers on the market	66281	12.8822	4.99443	2	38
MM	Number of mixed product suppliers on the market	66281	2.76890	1.049969	0	6

Table 2.2: Correlation Table

		1	2	3	4	5	6	7	8	9
1	*ConVar*	1								
2	*OrgVar*	**0.677**	1							
3	*PriLabel*	**0.2474**	**-0.0699**	1						
4	*HHI*	**-0.4601**	**-0.3572**	**-0.0375**	1					
5	*MeanPackage*	**0.5519**	**0.2041**	**0.6051**	**-0.1513**	1				
6	*DiscountShare*	**0.2184**	**0.0284**	**0.1951**	**-0.098**	**0.2154**	1			
7	*AdShare*	**0.2599**	**0.1129**	**0.2189**	**-0.055**	**0.1954**	**0.4723**	1		
8	*TotalQuantity*	**0.6143**	**0.6827**	**0.1057**	**-0.2408**	**0.2851**	**0.0904**	**0.1625**	1	
9	*StoRev*	**0.6263**	**0.6457**	**0.2225**	**-0.2187**	**0.3999**	**0.0447**	**0.1033**	**0.8832**	1

Notes. Bold denotes significance at $p < .05$ level.

2.4.2. Difference-in-Differences Analysis

2.4.2.1 The Effect of Introducing Organic Products

To assess the effect of introducing organic products on conventional product variety, we use a difference-in-differences regression. The main dependent variable is the variety of conventional product (*ConVar*) and the independent variables are binary treatment indicator of Treat and the binary indicator of the post-treatment After. We are interested in the interaction term of the above two binary variables. Conventional product variety could also be affected by unobserved store characteristics and market conditions. Therefore, we further control for organic supplier in the market (*OM*), conventional supplier in the market (*CM*), and mixed supplier in the market as our control (*MM*). We use a fixed effects model to control for non-time varying variables. Equation (2.2), below, shows the main model that estimates the effect of introducing organic product variety on conventional product variety.

$$ConVar_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 After_{it} + \beta_3 Treat_i * After_{it} + \boldsymbol{\gamma X_{it}} + \rho_i + \delta_t + \varepsilon_{it} \tag{2.2}$$

where i indexes store and t indexes week. X denotes the vector of control variables, including *PriLabel*, *HHI*, *StoRev*, *OM*, CM, and *MM*. δ_t denotes dummies for time-fixed effects, λ_i denotes dummies for store fixed effects, and ε_{it} is the error term. By controlling for both time and store fixed effects, we are able to account for all time invariant effects such as geographic area and store type as well as for any seasonal effects on product assortment decisions.

2.4.2.2 The Effect of Supply Chain Power

To assess the effect of how supply chain power affects the relationship between introducing organic products and the variety of conventional products, we further include the interaction of the supply chain power variables with the interaction of Treat and After and assess the three-way interaction terms. Specifically, Equation (2.3) and Equation (2.4) show the interaction effect of supplier concentration (*HHI*) and the effect of private-label ratio (*PlRatio*), respectively.

$$ConVar_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 After_{it} + \beta_3 logHHI_{it} + \beta_4 logHHI_{it} * Treat_i * After_{it} + \boldsymbol{\gamma X_{it}} + \rho_i + \delta_t + \varepsilon_{it} \quad (2.3)$$

$$ConVar_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 After_{it} + \beta_3 PlRatio_{it} + \beta_4 PlRatio_{it} * Treat_i * After_{it} + \boldsymbol{\gamma X_{it}} + \rho_i + \delta_t + \varepsilon_{it} \quad (2.4)$$

2.4.2.2 The Effect of Store Size Constraint

As discussed earlier, we use annual store revenue (*StoRev*) as the proxy of store size in our data. Similar to 2.4.2.2, we use the three-way interaction term among Treat, *After* and *StoRev* to assess the effect of how store size constraint would affect the relationship between introducing organic products and the variety of conventional products. Equation (2.5) below presents our model.

$$ConVar_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 After_{it} + \beta_3 StoRev_{it} + \beta_4 StoRev_{it} * Treat_i * After_{it} + \boldsymbol{\gamma X_{it}} + \rho_i + \delta_t + \varepsilon_{it} \quad (2.5)$$

We acknowledge that annual store revenue (*StoRev*) may not be the perfect measure for store size; therefore, we perform additional validations in the extension section 2.6.4.

2.5. Results

First, we report the results regarding the effect of introducing organic products and how supply chain power affects this relationship. Next, we check the robustness of our results.

2.5.1. Main Results

The difference-in-differences regression estimates of Equation (2.2) are reported in Table 2.3. First, we find that introducing organic products increases the conventional product variety (β_3= 11.59, p < .01). We also find that, through the three-way interaction, that stores with higher private-label ratio have lower conventional product variety after introducing organic products (β_4= -49.94, p < .05), while larger stores have higher conventional product variety after introducing organic products (β_4= 0.740, p < .05). The moderating effect of supplier concentration is not significant in our current model. We believe that this may be driven by the fact that the majority of our treatment stores source from existing suppliers when they first introduced organic products, and only a small portion of our treatment stores acquired a new supplier when they first introduced organic products. Sourcing from a new supplier may send out signals to existing suppliers that threatens the dependency of the retailer on the suppliers. Therefore, stores that already have less concentrated supplier (lower HHI) base would gain more negotiation power from introducing organic products and push for more conventional product variety from the existing conventional suppliers. On the other hand, sourcing from existing suppliers does not send out a signal of threatening the dependency on existing suppliers, therefore supplier concentration does not play a significant role in this case. To separate these two groups, we further perform two sets of analyses where we either keep treatment stores that used new suppliers (12 stores), or treatment stores that did not use new suppliers (69 stores). We first apply the same propensity score matching process on the 12 treatment stores that used new suppliers with all 431 control stores, and re-run Models (2.2) to (2.5). We then perform another propensity score matching on the 69 stores that did not use new suppliers with the same 431 control stores, and again re-run Models (2.2) to (2.5). Table 4 shows the result of these two sets of analyses. We could see that ("New Supplier" tab, (results (6)) stores with higher HHI have lower conventional product variety after introducing organic products (β_4= -31.78, p < .01). On the other hand, stores that did not use new supplies ("Existing Supplier" tab, result (11)) do not exhibit this effect.

2.5.2. Robustness Checks

We made changes in our propensity score matching process to see if our results are robust. First, we use three and one nearest neighbor matching instead of five nearest neighbors. For three nearest neighbor matching, we find consistent treatment effect (β_3= 13.69, *p* < .01), private-label ratio (β_4= - 59.41, p < .05), and store size effect (β_4= 0. 93, *p* < .01). For one nearest neighbor matching, we also find consistent treatment effect (β_3= 13.97, *p* < .01), private-label ratio (β_4= -56.57, *p* < .05), and store size effect (β_4= 0.94, *p* < .01). Although HHI effect is not significant using the full sample for three and one nearest neighbor matching as well, we find consistent effect of HHI when using the subsample of the 12 stores that used new suppliers for both three nearest neighbor matching (β_4= -23.66, *p* < .05) and one nearest neighbor matching (β_4= -24.47, *p* < .1).

Second, because our matching results in the main analysis may depend on the matching sequence, which starts the matching from week 1 up to week 208. Thus, it is possible that the quality of the matches declines in later weeks. Therefore, we may have a biased control group for the treatment stores that introduced organic products in the later phase of our time span. To ensure that our results are not affected by this potential bias, we rematch the treatment group and control group using reverse-time sequence (week

208 to 1). Our results show consistent effect of treatment effect (β_3= 10.80, p < .01), private-label ratio effect (β_4= -58.15, p < .05), and store size effect (β_4= 0.90, p < .1).

2.6. Extensions

In the main analysis, we examined the impact of introducing organic products on conventional product variety. As a first extension, using instrumental variables regression, we study the impact of increasing organic product variety on conventional product variety in Section 2.6.1 below.

6.1. Econometric Models and Estimation Strategy

Equation (2.6), below, shows the model that estimates the effect of organic product variety on conventional product variety

$$ConVar_{it} = \beta_0 + \beta_1 OrgVar_{it} + \boldsymbol{\gamma X_{it}} + \lambda_i + \delta_t + \varepsilon_{it} \qquad (2.6)$$

where i indexes store and t indexes week. $OrgVar_{it}$ represents the number of organic SKUs in store i at week t. In order to test the relationship between organic product variety and conventional product variety at the store level, we calculated the number of SKUs of organic yogurt sold in store i at week t as our main independent variable. X denotes the vector of control variables, as described above in Section 2.3.2.3. As before, δ_t denotes dummies for time-fixed effects, λ_i denotes dummies for store-fixed effects, and ε_{it} is the error term.

In our study, the number of organic yogurt SKUs ($OrgVar_{it}$) may not be an exogenous variable because a manager may carry a specific amount of variety of organic products on the basis of certain store and product characteristics that we are unable to observe. In addition, store managers may decide on their organic product offerings based on conventional product offerings. Therefore, there may be a reverse causal relationship between organic product variety and conventional product variety. In order to control for these potential endogeneity issues, we use a two-stage least squares (2SLS) regression to estimate Equation (2.6) above. In particular, we use the number of organic suppliers in the store as an instrument for organic product variety. Conceptually, organic products are supplied by organic product suppliers; therefore, the number of organic suppliers a store has relationship with could affect organic product variety. Thus, it satisfies the relevance requirement of an instrument variable. On the other hand, since organic suppliers do not have control on what conventional products are supplied to the store, the number of organic suppliers would not directly impact conventional product variety that a store offers. Thus, the exclusion requirement of an instrumental variable is also met.

We use fixed effects 2SLS panel data analysis, with standard errors clustered at the retail-chain level, to test the effect of organic product variety on conventional product variety. We cluster our standard errors at the retail-chain level because stores within the same chain may undertake similar operations, and therefore, the observations gathered from the same retail chain may be correlated. As explained above, the store fixed effects control for all time-invariant unobserved variables, such as store location and store size, and the time fixed effects control for seasonality.

Table 2.3: Main Results

Variable Names	(1) *ConVar*	(2) *ConVar*	(3) *ConVar*	(4) *ConVar*
After	-4.544***	-11.51	-5.097***	-6.409***
	(1.024)	(17.21)	(1.107)	(1.386)
*Treat*After*	11.59***	-55.78	17.07***	-2.016
	(2.855)	(95.21)	(4.885)	(3.267)
*Treat*HHI*		-53.43***		
		(14.55)		
*After*HHI*		0.909		
		(2.024)		
*Treat*After*HHI*		8.099		
		(11.68)		
*Treat*PlRatio*			-11.27	
			(37.05)	
*After*PlRatio*			27.83***	
			(8.951)	
*Treat*After*PlRatio*			-49.94**	
			(20.50)	
*Treat*StoRev*				1.357
				(4.285)
*After*StoRev*				0.309**
				(0.148)
*Treat*After*StoRev*				0.740**
				(0.296)
HHI	-0.682	2.952	-1.001	0.214
	(6.286)	(3.708)	(6.463)	(6.072)
PlRatio	-59.65*	-64.08*	-70.66*	-58.58*
	(34.00)	(33.27)	(37.51)	(33.01)
StoRev	0.149	-0.0637	0.0186	-1.563
	(0.656)	(0.759)	(0.623)	(4.314)
OM	-0.892	-0.757	-0.917	-0.601
	(0.631)	(0.688)	(0.667)	(0.633)
CM	-2.377***	-2.046***	-2.253***	-2.176***
	(0.415)	(0.381)	(0.417)	(0.394)
MM	-0.144	-0.169	-0.115	-0.137
	(0.760)	(0.776)	(0.732)	(0.772)
Observations	48,446	48,446	48,446	48,446
R-squared	0.329	0.356	0.340	0.349
Number of iri_key	302	302	302	302
Store/Week FE	YES	YES	YES	YES

Notes. * p < .10, ** p < .05, *** p < .01. Clustered Robust Standard errors in parenthesis.

Table 2.4: Introducing Organic Products from A New Supplier

	New Supplier				Existing Supplier			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*ConVar*	*ConVar*	*ConVar*	*ConVar*	*ConVar*	*ConVar*	*ConVar*	*ConVar*
*Treat*After*	6.526*	265.3***	19.29*	11.50	11.17***	-94.22	16.12***	-5.243
	(3.781)	(64.04)	(10.52)	(7.693)	(3.548)	(107.1)	(5.797)	(3.802)
*Treat*After*HHI*		-31.7***				12.75		
		(7.819)				(13.15)		
*Treat*After*PlRatio*			-62.26*				-47.69*	
			(33.06)				(24.15)	
*Treat*After*StoRev*				-0.542				0.874***
				(0.424)				(0.258)
PlRatio	-72.34**	-71.81**	-88.45**	-71.86**	-64.37**	-67.9***	-67.4***	-61.11**
	(28.38)	(28.23)	(34.43)	(28.52)	(24.09)	(23.00)	(18.69)	(22.77)
StoRev	1.533	1.668	1.727	0.572	0.609	0.478	0.460	0.493
	(2.589)	(2.540)	(2.591)	(2.647)	(0.509)	(0.603)	(0.516)	(2.987)
HHI	-0.0559	-0.500	-0.500	0.530	0.179	4.561	-0.355	0.926
	(7.284)	(5.845)	(7.193)	(7.051)	(6.516)	(3.744)	(6.668)	(6.438)
Observations	23,046	23,046	23,046	23,046	45,753	45,753	45,753	45,753
R-squared	0.354	0.362	0.364	0.357	0.334	0.361	0.349	0.360
Number of Store	143	143	143	143	279	279	279	279
Store/Week FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes. * p < .10, ** p < .05, *** p < .01. Clustered Robust Standard errors in parenthesis. Some variables are omitted for brevity.

Equation (2.7), shown below, is used to test the moderating effect of private-label on the relationship of organic product variety with conventional product variety. Thus, the coefficient of the interaction term becomes our variable of interest.

$$ConVar_{it} = \beta_0 + \beta_1 OrgVar_{it} + \beta_2 PriLabel_{it} + \beta_3 OrgVar_{it} * PriLabel_{it} + \boldsymbol{\gamma X_{it}} + \lambda_i + \delta_t + \varepsilon_{it} \quad (2.7)$$

It should be noted that the interaction term may be endogenous because of the potential endogeneity of organic product variety, as explained above. We use additional instrumental variables to address the endogeneity of the interaction variable. In particular, we use the interaction of $PriLabel_{it}$ with the instrumental variable (number of organic suppliers) as an instrument for the interaction variable (Wooldridge, 2010). Therefore, we use two instruments for two potentially endogenous variables ($OrgVar_{it}$ and $OrgVar_{it}$* $PriLabel_{it}$).

Equation (2.8), given below, tests the moderating effect of the HHI.

$$ConVar_{it} = \beta_0 + \beta_1 OrgVar_{it} + \beta_2 logHHI_{it} + \beta_3 OrgVar_{it} * logHHI_{it} + \boldsymbol{\gamma X_{it}} + \lambda_i + \delta_t + \varepsilon_{it} \quad (2.8)$$

Similar to the estimation of Equation (7), we use two instrumental variables for two potentially endogenous variables ($OrgVar_{it}$ and $OrgVar_{it}$ *HHI_{it}).

2.6.2. Results for Instrumental Variables Regression

We performed VIF tests to check for potential multicollinearity issues. We find that the VIFs for *MeanPackage* and *TotalQuantity* are 48.31 and 10.45, respectively. As the high VIF scores raise concern for multicollinearity, we dropped these two control variables (*MeanPackage* and *TotalQuantity*) and reran our analysis. The mean VIF after dropping these two variables is 4.30 and no variable VIF exceeds the value of 10. Therefore, multicollinearity is no longer a concern in our model.

Table 2.5 (result (13)) shows that the effect of organic product variety on conventional product variety is positive and highly significant (β_1= 0.9708, p < .01), which suggests that an increase in organic product variety is associated with an increase in conventional product variety in stores. In addition, we translate the coefficient to elasticity by $e = \beta * \frac{X}{Y}$. Using the average values of organic product variety and conventional product variety for X and Y, respectively and using β_1= 0.9708, the elasticity of our model is 0.094. This implies that conventional product variety increases, on average, by 0.094% for a 1% increase in organic product variety.

Table 2.5, Result (14), shows a negative coefficient (β_3= -3.9745, $p < .01$) of the interaction term between organic product variety and the private-label ratio. Thus, the private-label ratio negatively moderates the association between organic product variety and conventional product variety. The total effect of organic product variety on conventional product variety in stores that hold private-label products is $\beta_1 + \beta_3 * PriLabel_{it}$. When the private-label variety ratio is less than 41.8% (i.e., 1.6628-3.9745 * $PriLabel_{it} = 0$ and $PriLabel_{it} = 0.418$), additional organic product variety would increase conventional product variety in the store. However, if the private-label variety ratio is greater than 41.8%, increasing organic product variety would lead to a decrease in conventional product variety. To further illustrate this finding, we plot the marginal effects of organic product variety. As shown in Figure 2.3, the average marginal effect of organic product variety decreases as the private-label ratio increases. The average marginal effect of organic product variety even becomes negative when the private-label ratio exceeds 0.418. As a further example, consider two stores: each with 30 organic product SKUs. One store has a private-label product ratio of 35% while the other has a private-label ratio of 45% (see Figure 2.4). When both stores increase their organic product SKUs from 30 to 60, we can see that the number of conventional product SKUs in the second store decreases. This is because retail stores would prioritize both organic products and their store brands over branded conventional products. We discuss this effect further in Section 2.6.5.

Table 2.5: Instrumental Variable Regression

Variable Names	(13) *ConVar*	(14) *ConVar*	(15) *ConVar*
OrgVar	0.9708***	1.6628***	23.519***
	(0.1096)	(0.1923)	(1.1632)
*OrgVar*PriLabel*		-3.9745***	
		(0.7939)	
PriLabel	-111.81***	-81.232***	-126.46***
	(7.6247)	(9.8355)	(7.9874)
*OrgVar*HHI*			-2.8761***
			(0.1453)
HHI	-4.7025*	-5.6601**	15.479***
	(2.4093)	(2.4006)	(1.9414)
StoRev	1.3859***	1.2929***	0.8366*
	(0.4484)	(0.4347)	(0.4512)
DiscountShare	-0.8681**	-0.8386*	-0.3684
	(0.4396)	(0.4348)	(0.3896)
AdShare	0.6611	0.3881	1.4267**
	(0.6404)	(0.6345)	(0.6433)
Observations	307,688	307,688	307,688
R-squared	0.119	0.138	0.173
Number of Store	1,887	1,887	1,887
Store FE	YES	YES	YES
Week Dummy	YES	YES	YES

Notes. * $p < .10$, ** $p < .05$, *** $p < .01$. Clustered Robust Standard errors in parenthesis.

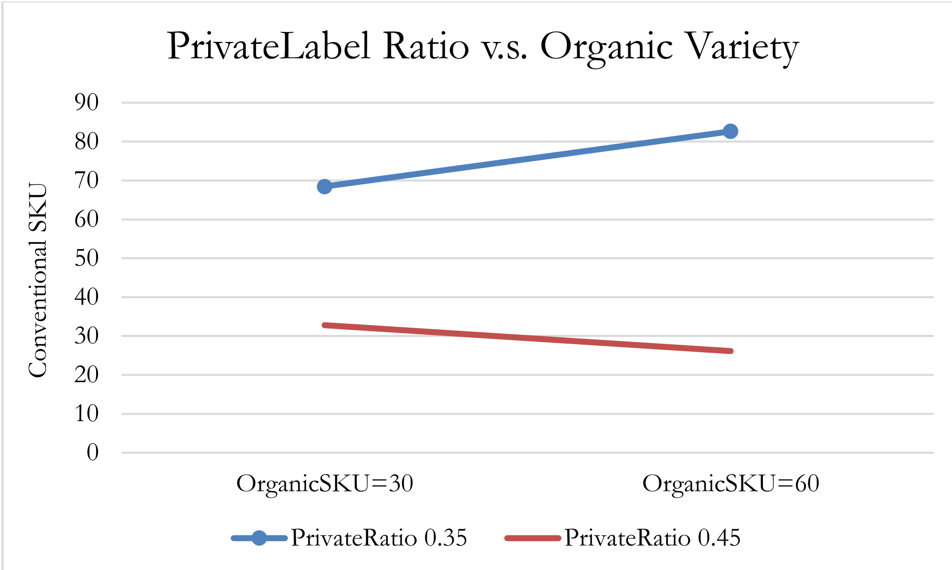

Figure 2.3: The Marginal Effect of Organic Variety
When Private-label Ratio Increases

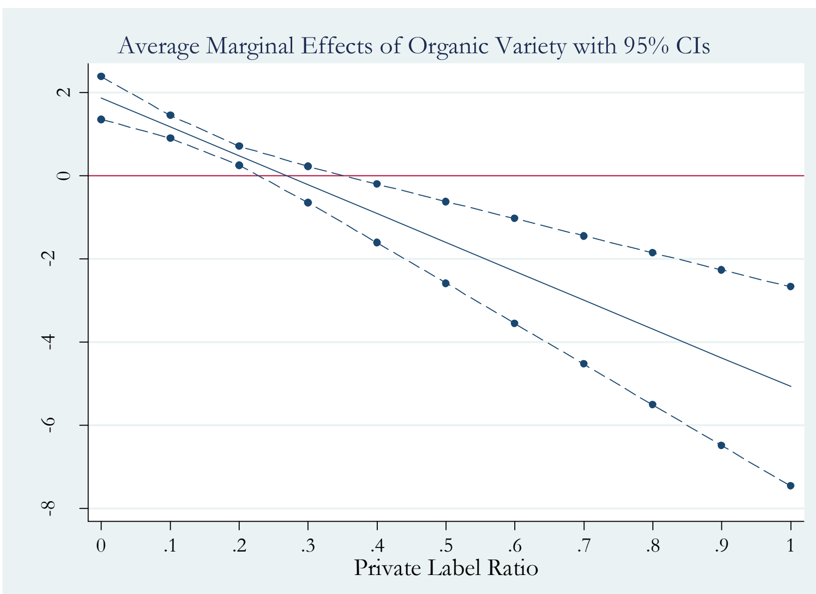

Figure 2.4: The Moderating Effect of Private-label

Table 2.5, Result (15), shows a negative coefficient (β_3= -2.8761, p < .01) of the interaction term between organic product variety and retail-chain HHI. When the revenue of a retail chain is highly concentrated with a few manufacturers, the manufacturers have more power on deciding a store's SKU offerings. As a result, retail chains offer fewer conventional product SKUs when introducing organic product SKUs, and manufacturers save on operating costs by managing fewer SKUs. On the other hand, when a retail chain is less concentrated, the retailers have more power deciding on their product variety offerings. They choose to offer more SKUs to attract more customers and generate higher revenue. Again, to illustrate this finding graphically, we plot the marginal effects of organic product variety when the HHI increases. As shown in Figure 2.5, when the HHI increases, the marginal effect of organic product variety decreases. The average marginal effect of organic product variety becomes negative when HHI is higher than 8.17 (i.e., 23.519-2.8761 **HHI*= 0 and *HHI*= 8.17).

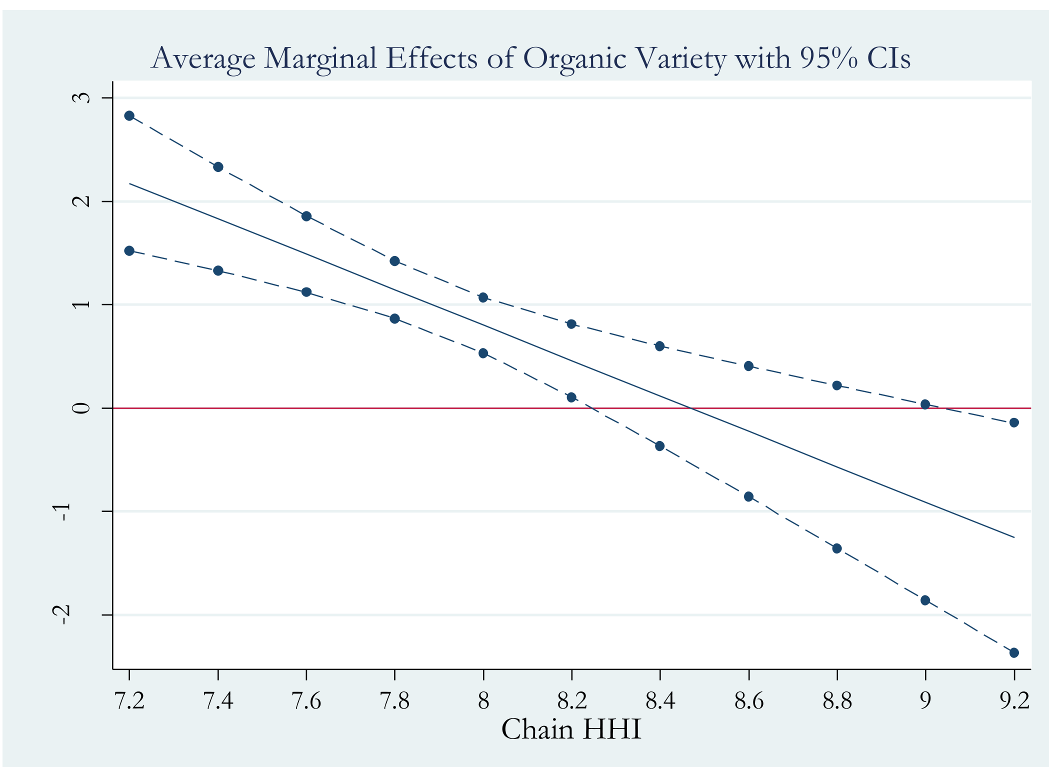

Figure 2.5: The Marginal Effect of Organic Variety When HHI Increases

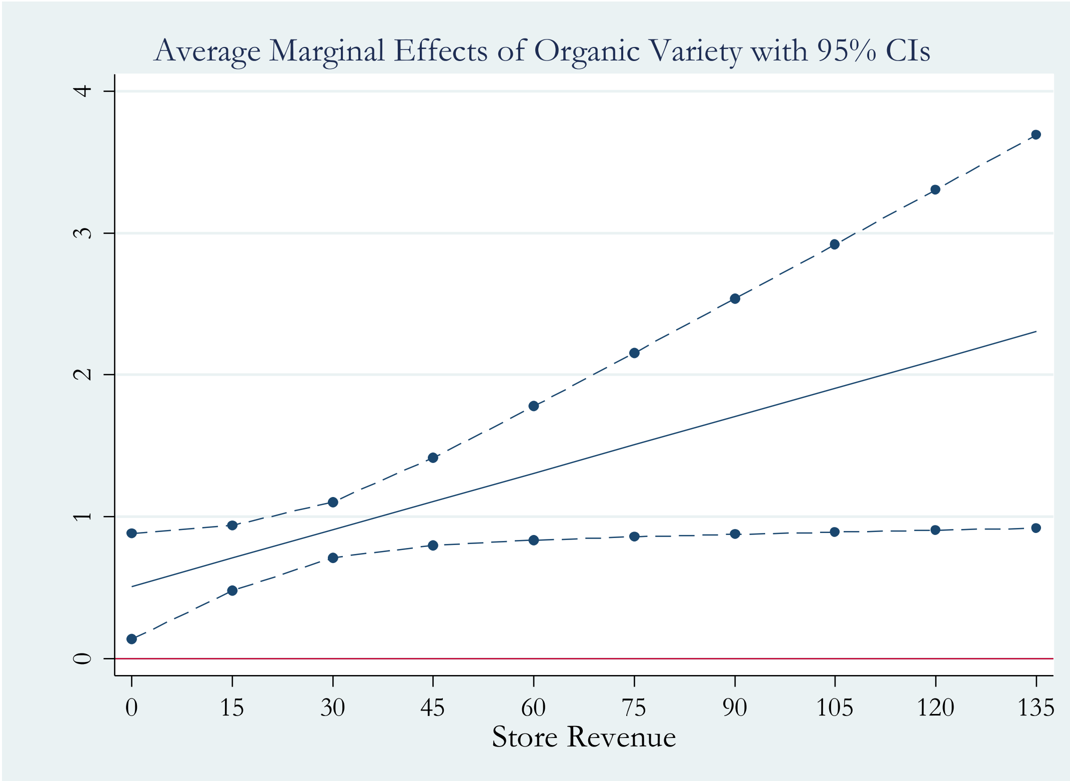

Figure 2.6: The Marginal Effect of Organic Variety When Store Size Increases

2.6.3. Store Size as a Constraint

We have showed that conventional product variety is positively associated with organic product variety, which supports the notion of a stronger market-expansion effect of organic product growth rather than a cost-efficiency effect. However, the market expansion effect is not necessarily in conflict with the cost-efficiency effect. In fact, the cost-efficiency effect becomes dominant when capacity constraints are sufficiently tight, in which case organic product and conventional product variety cannot continue to grow at the same time. Given the limited shelf space available to display yogurt, smaller stores are constrained by the number of SKUs (organic or conventional) that they can carry on their shelves. Larger stores have more space and therefore have more flexibility in adding SKUs. The previous analysis controls for store revenue as a proxy for store size or capacity. The positive relationship between organic product and conventional product variety, however, may be an artifact of our dataset having a large number of stores that are less constrained for capacity. In order to further examine the relationship between organic product and conventional product variety under capacity constraints, we consider an interaction term between store annual revenue (*StoRev*) and organic product variety (*OrgVar*). We recognize that store revenue is not a perfect measure for store size. However, we believe that larger stores generally would have higher revenues than smaller stores. We start our analysis using the full sample and use store annual revenue (*StoRev*) as a proxy for shelf space. Again, as in section 2.6.1, we use the same two instruments for the two potentially endogenous variables, and we employ 2SLS estimation. Result (16) of Table 2.6 shows the full sample coefficients. However, the interaction coefficient (β_3= 0.018, p = .27) is only qualitatively positive. One scenario that compromises the relationship between store size and revenue is market size and demand. For example, a smaller store located in a high population density area may have greater annual revenue than a larger store located in a low population density area. To alleviate this concern, we develop a subsample with similar market sizes to reduce the impact of differences in store traffic. Specifically, we identify the five most populated areas in our dataset: New York, Philadelphia, Washington, D.C., Chicago, and Los Angeles. The sizes of these markets are comparable. The results from the first subsample are compared with those from the full sample, and are shown in Results (17) of Table 6. We find that the interaction term (β_3= 0.01625, p < .1) is positively correlated with conventional yogurt variety. To illustrate it graphically, we plot the marginal effects of organic product variety as store revenue increases. As shown in Figure 2.6, when store revenue increases, the average marginal effect of organic product variety also increases. Finally, we also develop subsamples based on store revenue, with the bottom 5% of stores. In the bottom 5% stores, there are 178 stores with an average annual revenue of 2.52 (million $), ranging from 0.11 to 3.35 (million $). We use 2SLS estimation to analyze the impact of organic product variety on conventional product variety. Table 7, results (18) show the correlation (β_1= -1.118, p < .01) is negative. We also perform similar analysis for our diff-in-diff sample where we kept only bottom 5% of treatment stores (3 treatment stores) with all control stores and use diff-in-diff analysis with propensity score matching. Table 2.7, results (19) show that the interaction term between Treat and After is negative, which is consistent with the instrument variables estimation. Together, these findings indicate that smaller stores have significant space constraints that would not allow them to increase conventional product variety. These results reconcile our main result finding a positive relationship between organic product variety and conventional product variety with the more conventional, capacity-based cannibalization argument.

2.6.4. Branded Conventional Product Variety vs. Private-label Conventional Product Variety

Previously, we had shown that conventional yogurt variety decreases as organic yogurt variety increases in stores that have a strong presence of private-label products. In this section, we perform two additional analyses to further examine this relationship. In particular, we generate two variables: $BrdConVar_{it}$ and $PriConVar_{it}$.

Table 2.6: Five largest markets versus full sample

Variable Names	(16) *ConVar*	(17) *ConVar*
OrgVar	0.4411	0.7675
	(0.4695)	(0.4752)
*OrgVar*StoRev*	0.01800	0.01625*
	(0.01646)	(0.008394)
PlRatio	-110.68***	-112.14**
	(24.144)	(49.865)
HHI	-4.9663	-1.4389
	(18.073)	(22.090)
DiscountShare	-0.8172	0.4950
	(1.4863)	(2.3335)
AdShare	0.6305	-3.4741
	(2.4297)	(2.1412)
StoRev	0.8109	3.8301
	(0.8869)	(5.1476)
Observations	307,688	85,009
R-squared	0.124	0.087
Number of iri_key	1,887	537
Store/Week FE	YES	YES

Notes. * $p < .10$, ** $p < .05$, *** $p < .01$. Clustered Robust Standard errors in parenthesis.

Table 2.7: Bottom 5% Store Size

Variable Names	(18) *ConVar*	(19) *ConVar*
OrgVar	-1.118***	
	(0.0983)	
*Treat*After*		-1.850***
		(0.275)
HHI	-0.164*	-0.614
	(0.0856)	(0.319)
PlRatio	5.078***	9.785***
	(0.348)	(0.239)
StoRev	1.074	-2.229
	(0.702)	(6.680)
Observations	15,917	20,175
R-squared	0.299	0.087
Number of iri_key	187	142
Store FE	YES	YES
Week Dummy	YES	YES

(Some Control Variables Are Omitted for Brevity)
Notes. * $p < .10$, ** $p < .05$, *** $p < .01$. Clustered Robust Standard errors in parenthesis.

The former represents the number of branded conventional product variety that store i carries at week t, and the latter represents the number of private-label conventional product variety that store i carries at week t. We estimate these two additional analyses using Model (6) and change the dependent variable to $BrdConVar_{it}$ and $PriConVar_{it}$, accordingly. The results are shown in Table 2.8 (Results (20) and (21), respectively). In Result (20), we can see that the interaction term between organic product variety and private-label ratio, β_3= -7.773 (p < .01), is negative. Thus, the private-label ratio negatively moderates the correlation between organic product variety and branded conventional product variety. The total effect of organic product variety on branded conventional product variety in stores that hold private-label product is $\beta_1+\beta_3$ * $PrivateLabel_{it}$. When the private-label variety ratio is less than 28.2% (i.e., 2.194-7.773 * $PrivateLabel_{it}$ = 0, and $PrivateLabel_{it}$ = 0.282), additional organic product variety would increase branded conventional product variety in the store. However, if the private-label variety ratio is greater than 28.2%, increasing organic product variety would lead to a decrease in branded conventional product variety. However, in Result (21), we see a different effect on private-label conventional yogurt. The interaction term between organic product variety and the private-label ratio, β_3= 2.158 (p < .01), is positive. Thus, the private-label ratio positively moderates the correlation between organic product variety and private-label conventional product variety. The total effect of organic product variety on branded conventional product variety in stores that hold private-label product is $\beta_1+\beta_3$ * $PrivateLabel_{it}$. When the private-label variety ratio is higher than 9.4% (i.e., -0.203+2.158 * $PrivateLabel_{it}$ = 0 and $PrivateLabel_{it}$ = 0.094), additional organic product variety would increase private-label conventional product variety in the store. And only when the private-label variety ratio is less than 9.4%, additional organic product variety would decrease private-label conventional product variety in the store. These additional analyses point to the fact that retailers with strong private-label presence tend to reduce branded conventional product variety when increasing organic product variety.

Table 2.8: Private or Branded Conventional Variety

Variables	(20) *BrdConVar*	(21) *PriConVar*
OrgVar	2.1937***	-0.2033***
	(0.384)	(0.065)
*OrgVar*PriLabel*	-7.7725***	2.1577***
	(2.071)	(0.408)
PriLabel	-165.31***	66.610***
	(20.199)	(14.368)
DiscountShare	-1.7408	0.2490
	(1.943)	(0.554)
AdShare	8.615e-04***	1.081e-04*
	(2.945e-04)	(6.197e-05)
StoRev	1.2197**	0.01947
	(0.108)	(0.104)
Observations	246,659	246,659
R-squared	0.279	0.378
Number of Store	1,540	1,540
Store FE	YES	YES
Time FE	YES	YES

Notes. * $p < .10$, ** $p < .05$, *** $p < .01$. Clustered Robust Standard errors in parenthesis.

2.6.5. Greek Yogurt and All-Natural Yogurt Subcategories

Another concern associated with our results is that, instead of organic products, there may be other trendy products that spike conventional product variety in our study period. In this section, we aim to rule out such a possibility. During our time period of study, the rapid growth of organic yogurt coincided with the launch and soaring popularity of Greek yogurt and All-Natural yogurt. The varieties of these two subcategories increased significantly during the same time. A natural possibility could be that if Greek yogurt and All-Natural yogurt are mostly conventional products, then the increase in conventional yogurt variety might be a result associated with the popularity of these two subcategories, rather than because of the increase in organic yogurt variety. To rule out this alternative explanation, we control for product variety of these two subcategories, and re-estimate the previous models. Because Greek yogurt and All-Natural yogurt are available as conventional and organic yogurts, we use the number of organic yogurt SKUs, excluding those for Greek yogurt and All-Natural yogurt to avoid multicollinearity issues (see Equations (2.9) and (2.10), respectively). The results are given in Table 2.9 (see Results (22) and (23)). We find that after controlling for the variety of these subcategories, organic product variety is still positively associated with conventional product variety (β_1= 0.657, $p < .01$ and γ_1= 1.047, $p < .01$). We further find that the effect size of Non-Greek organic yogurt is 0.058, indicating that conventional yogurt variety increases 0.058% when Non-Greek organic yogurt variety increases 1%. Similarly, the effect size of Non-Natural organic yogurt is 0.097, indicating that conventional yogurt variety increases 0.097% when Non-Natural organic yogurt variety increases 1%.

$$ConVar_{it} = \beta_0 + \beta_1 OrgNonGreekVar_{it} + \beta_2 GreekVar_{it} + \boldsymbol{\sigma X_{it}} + \lambda_i + \delta_t + \varepsilon_{it} \quad (2.9)$$

$$ConVar_{it} = \gamma_0 + \gamma_1 OrgNonNaturalVar_{it} + \gamma_3 AllNaturalVar_{it} + \boldsymbol{\sigma X_{it}} + \lambda_i + \delta_t + \varepsilon_{it} \quad (2.10)$$

These results indicate that while the emergence of new yogurt categories contributes to the increase in conventional product variety, the positive relationship between organic and conventional product variety remains significant.

Table 2.9: Alternative Explanation: Greek Yogurt and All-Natural Yogurt

Variables	(22) *ConVar*	(23) *ConVar*
OrgNonGreekVar	0.657***	
	(0.131)	
GreekVar	1.002***	
	(0.078)	
OrgNonNaturalVar		1.047***
		(0.124)
NaturalVar		0.547*
		(0.323)
Observations	307,697	307,697
R-squared	0.658	0.519
Number of Store	1,896	1,896
Store FE	YES	YES
Week Dummy	YES	YES

(Some Control Variables Are Omitted for Brevity)
Notes. * $p < .10$, ** $p < .05$, *** $p < .01$. Clustered Robust Standard errors in parenthesis.

2.6.6. DOES HIGHER PRODUCT VARIETY LEAD TO GREATER SALES?

While our main analysis provides solid support for our main results, it does not address the possibility that the increases in product variety may not be accompanied by increases in sales. In such case, the pie is indeed larger, but it is also thinner because larger number of customers may not result in additional sales. To test this, we focus on the category revenue of yogurt products. Category revenue has been studied in the past literature (e.g., Perdikaki et al., 2012). Note that changes in yogurt revenue may be driven by the potential upward trend in consumer demand for yogurt products, which is measured by the per capita consumption of yogurt (YPCC) . We control for this trend using the per capita consumption of yogurt (YPCC) in the United States from 2008 to 2011 (in pounds per person, retrieved from the Statista Portal). After controlling for

YPCC, we test the relationship between organic product variety (and conventional product variety) and store-level yogurt sales.

$$YogurtRevenue_{it} = \beta_0 + \beta_1 OrgVar_{it} + \beta_2 ConVar_{it} + \beta_3 YPCC_t + \gamma X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \quad (2.11)$$

We present our findings in Table 2.10, Result (24). As can be gleaned from this table, both organic product variety (β_1= 16.67, p < .01) and conventional product variety (β_2= 4.009, p < .05) are positively correlated with yogurt revenue. The effect size of organic variety and conventional variety are 0.04 and 0.10, respectively. These results indicate that a 1% variety increase in organic products will lead to 0.04% increase in store yogurt sales, while 1% variety increase in conventional products will lead to 0.1% increase in store yogurt sales.

Table 2.10: Store Traffic Extension

Variables	(24) *YogurtRevenue*
ConVar	4.009**
	(1.617)
OrgVar	16.67***
	(3.628)
YPCC	66.16
	(61.948)
Observations	206,719
Number of Store	1,263
R-squared	0.926
Store FE	YES
Week Dummy	YES

(Some Control Variables Are Omitted for Brevity)
Notes. * *p* < .10, ** *p* < .05, *** *p* < .01. Clustered Robust Standard errors in parenthesis.

2.7. Discussion and Conclusions

In this study, we seek to address two questions: (1) Does conventional product variety increase or decrease when organic product is introduced (or organic product variety increases)? (2) Does the control of assortment decisions in the supply chain affect assortments between organic and conventional products? Our findings show that introducing organic products will result in an increase of conventional product variety. This positive relationship between organic product introduction and conventional product variety is largely attributed to the growing segment of organic product consumers. These organic product customers are not only drawn to stores that start introducing or increasing their existing organic product offerings, but they will also likely purchase conventional products that are attractive to them during their shopping trips. It is also important to note that an increase in conventional product variety is not indefinite. Our main finding suggests that the market expansion effect of organic products largely outweighs the increases in operational costs for average retailers. However, we also show that stores that face limited shelf-space resources tend to reduce conventional product variety to make room for organic products when they introduce or expand their organic product offerings. This is consistent with the literature that suggests that product assortment is constrained by the space available in stores (Corstjens & Doyle, 1981).

Extending our findings to include the supply chain relationship effects, we also find that when manufacturers are more concentrated, and therefore more powerful in the supply chain and have control over product assortment decisions, stores tend to have a less positive relationship between organic product and conventional product variety. This finding supports the theoretical result that powerful manufacturers may strategically reduce product variety to reduce costs (Inderst & Shaffer 2007). Similarly, when retailers are more powerful with a strong private-label presence (Dunne & Narasimhan, 1999; Narasimhan & Wilcox, 1998; Quelch & Harding, 1996), they tend to reduce branded conventional products and increase private-label conventional products when introducing organic products. This suggests that retailers further leverage their store brands and supply chain control in their assortment decisions, leading to asymmetric effects of organic products on conventional product variety. Taken together, these findings suggest that retailers tend to increase conventional product offerings with the introduction of organic products, as long as they have enough capacity and have control over the supply chain.

2.7.1. Theoretical Implications

Retail store operations face a variety of novel challenges and complexities (Mou et al., 2018). Our research contributes to the product assortment literature by empirically examining the impact of an emerging product type—organic products—on retailer product assortment decisions. Increasing product variety generally has two effects on retail operations. On the one hand, there is the revenue effect from better market segmentation, by attracting new and variety seeking consumers (Bayus & Putsis, 1999; Ton & Raman, 2010; Xia & Rajagopalan, 2009). However, retailers should also be aware of the cannibalization effects as product variety increases (Quelch & Kenny, 1994). This happens when a product in a certain category may cannibalize consumer demand of another product in the same category. Our results indicate that, organic products, thanks to their specialized group of customers, stimulate the demand for a variety of conventional products within the same category. Therefore, introducing and increasing organic product offerings are different from traditional decisions pertaining to product line extensions. On the other hand, there is the cost effect associated with operations increasing product variety (Mantrala et al., 2009; Shockley et al., 2015). We also confirm that the cost effect is significant when retailers face strict shelf space constraints, as well as when the market expansion effect is subject to capacity constraints (Hamilton & Richards, 2009).

In addition, manufacturers bear much higher cost from increasing product variety compared to retailers (Kekre & Srinivasan, 1990; Fisher & Ittner, 1999), and in particular, with respect to organic products (Chang & Schuster, 2002). Therefore, as organic products continue to gain momentum in the market, the governance and control in the organic product supply chain become more important for retailer assortment decisions. We contribute to the literature by empirically examining the effect of organic supply chain governance and control on retailer-manufacturer product assortment decisions. In particular, we consider supply chains that contain a concentrated group of manufacturers or a retailer with strong private-label presence. We show that these two mechanisms lead to different results for conventional product variety. With a smaller, concentrated manufacturer group, the retailer has less power and control over product assortment decisions. We show that a manufacturer's concerns of cost efficiency associated with organic products have a stronger effect on retailer assortment decisions, thereby mitigating the market expansion effect for manufacturer brands. Moreover, we show that retailers with a strong private-label presence may leverage the pattern of expansion of organic product variety as an opportunity to increase their private-label conventional products and reduce their reliance on national brand conventional product variety. Prior research on private-label products mostly focuses on product and service quality, customer loyalty, store differentiation, and store profitability in the context of supply chain governance and control (Ailawadi et al., 2008; Chintagunta et al., 2002; Corstjens & Lal, 2000; Martos-Partal & González-Benito, 2011). In contrast, we empirically show that private-label products also play a role in supply chain relationship through the retailers' assortment planning decisions. Our finding of retailers switching national brand conventional products with private-label products when introducing organic products is consistent with other studies. For example, Alan et al. (2017), found that retailers would protect their private-label products by reducing competing national branded product assortments. We build further on Alan et al.'s (2017) work by showing that retailers will strategically use organic product expansion as an opportunity to strengthen their private-label product portfolio as well. Taken together, these findings suggest that the growth of organic products is demand-driven and motivated by an increasing variety-seeking customer base, which stimulates an assortment involving a higher variety of conventional product offerings. However, the supply-driven constraints and cost implications in the supply chain significantly affect this relationship as well. This is true especially when manufacturers have more power to influence product assortment decisions.

2.7.2. Managerial Implications

In addition to the contributions to theory, this study has managerial implications as well. For retailers that have not yet launched organic products on their shelves, this study points to the benefit of overall store sales from the introduction of organic products. Retailers could use organic products to attract new variety-seeking consumers, who could also buy conventional products as well. This way stores are also encouraged to add variety for conventional products also. Increasing both organic product variety and conventional variety will result in higher category level sales. To be more specific, our results show that a 1% increase in organic product variety could lead to a 0.04% increase in total category sales. Similarly, by increasing conventional product variety by 1% would lead to a 0.1% increase in total category sales. As the contingent nature of our findings indicate, it is not a "free lunch," that is, there is a tapering off effect of further increasing product variety. First, the limited shelf space may limit retailers' ability to further increase total product variety. In such cases, retailers will have to switch some of their low-performing conventional products with organic products. Another constraint comes from the supplier side: a concentrated supplier base also hinders retailers from increasing total product variety. Because increasing product variety increases costs for manufacturers more than for retailers, such factors should be carefully considered when deciding on the optimal mix of organic product variety in comparison to variety of conventional products. On the flip side, if retailers face adverse power from manufacturers, they can respond by introducing private-label brands. Because private-label products help retailers gain customer loyalty, introducing private-label products would enhance retailers' power in the supply chain. In addition, retailers that already have private-label products can further enhance their power in the supply chain by substituting national brand conventional products with private-label conventional products as they attempt to increase organic product variety. As a result, retailers could introduce their private-label products to the newly acquired organic product customers and gain loyalty from these organic product customers. Viewed from a manufacturer's perspective, by facing the growing pressure of supplying organic products and meeting retailers' demand for more variety in conventional products, manufacturers should invest in clear product differentiation of their national brands (for organic and conventional products) so that customers can be wooed away from the retail stores' organic or private-label brands. In addition, since producing both conventional products and organic products may be costly, manufacturers could consider mergers and acquisitions with small organic product producers, thereby increasing their overall product portfolios.

2.7.3. Limitations and Future Research

Our study is not without limitations. First, we should note that organic consumers also purchasing conventional products may be driven by the fact that organic product supply is still limited. Therefore, many product variants are available only in conventional product forms. As organic production gets more generalized, organic consumers may become more exclusive in their purchasing patterns of organic products. If this is the case, we may see a decrease in the positive correlation between organic product and conventional product variety in the future. However, as the supply of organic products is still very limited today, we do not expect such effects to diminish in the near future. Second, we did not have a precise measure for shelf space. Although using store revenue is a reasonable proxy for shelf space, future research could use actual shelf space data to understand to what extent shelf space constrains the growth of conventional products. Third, we use only yogurt data to study the effects of organic product growth on conventional products due to the limitation of our data source. As organic products become less expensive to consumers, future research could use more product categories and see if the balance between product expansion and cost efficiency is different across product categories. Fourth, our sample is limited to the United States of America. European countries have a slightly more mature organic market, while Asian countries have just begun to introduce organic products into the retail market in a formal manner. Future research with data from different countries and regions may provide richer insights into how organic products perform differently across global regions. Finally, we did not have data on all organic product manufacturers and the unmasked names (real identities) for the retail chains. Future research conducted with additional identity related information may provide valuable contextual insights on how different manufacturers and retailers react to the growth in organic products.

CHAPTER 3

HOW DO CONSUMERS CHOOSE BETWEEN ORGANIC PRODUCTS AND MULTIPLE PRODUCT ATTRIBUTES? AN EMPIRICAL STUDY OF YOGURT SALES

ABSTRACT

The rapid growth in organic product variety poses challenges for retailers to manage their assortment mix. Although organic consumers are willing to pay a higher price for organic products, more and more evidence shows that organic consumers are also price-sensitive. In addition, when choosing between organic and conventional products, consumers face a much more complex decision that involves product brand, style, and other specific product attributes than a binary choice between organic and conventional product types. However, an in-depth understanding of how consumers make such complex decisions involving organic and other product attributes is missing. In this study, we use scanner panel data from retailers across the united states to examine how customers evaluate organic products when there are a large number of other product attributes present at the same time. In particular, we estimate own-price and cross-price elasticities under different nesting options. Our findings suggest that organic condition, product style, and seller attributes are all highly influential in shaping consumers' purchasing decisions. Further, the relationship between organic and conventional products is much more nuanced and context-specific than previously shown. Counter-

intuitively, we find products that are most appealing to health-conscious consumers are also the ones that are most prone to price changes. Through this finding, we are able to provide insights to retailers that offer both organic and conventional products on how to manage their assortment mix.

Keywords: Organic Products, Choice Modeling

3.1. INTRODUCTION

In the last decade, the U.S. organic market has more than doubled in size (Organic Trade Association, 2018; see Figure 1.1). Driven by the growing number of health-conscious consumers, conventional grocers have significantly increased their assortment of organic products in recent years . As a result, retailing organic food changed as traditional purveyors of organic food faced increased competition from companies new to the sector, with organic food sold not only in natural-products stores, such as Whole Foods and food cooperatives, but also in traditional supermarkets such as Safeway, big-box stores such as Wal-Mart, and club stores such as Costco (Dimitri & Oberholtzer, 2009).

Although organic products are typically priced higher than their conventional counterparts, sales of organic products and especially organic produce are booming. The organic premiums, defined as “the price difference between the organic and the nonorganic price of an item when factors such as the type of store sold, time of year and geographic location are the same” (ERS, 2016), ranged from 7 percent for fresh spinach to 60 percent for salad mix. This premium does not necessarily deter sales. For example, 17 percent of people who purchase organic at least sometimes were willing to pay up to 35 percent more for organic vegetables, and 27 percent were willing to pay 20 to 34 percent more (The Hartman Group. 2016). It is believed that organic consumers are much less price-sensitive (Enneking, 2002; Mondelaers et al., 2008) than non-buyers. However, recent studies suggest that although the “hardcore” organic consumers may be less price-sensitive, the majority of organic consumers do care about organic pricing. A 2009 study by the Hartman Group found that there are three key consumer demographics: While 21% of the total consumers buy organic products exclusively, 65% of the total consumers buy both organic products and conventional products. The “occasional” organic consumers bring both opportunities and challenges to conventional supermarkets. On the one hand, carrying non-organic (we refer it as “conventional” hereafter) products may reduce the loss of sales when a specific organic product is not available. On the other hand, retailers should also beware of low-margin conventional products cannibalize the sales of high-margin organic products. Therefore, it is important to understand how consumers choose between organic and conventional products and how much does conventional products cannibalize the sales of organic products. Especially for those retailers who carry both types of products.

Along with the rapid growth of organic products, new product features have also emerged and prospered. For example, Greek yogurt, no matter organic or conventional, who has a total of $60 million market in the United States back in 2005 turns $1.5 Billion in 2011 . As new products and product features emerge almost every day, grocery stores today carry 40,000 more items than they did in the 1990s (Malito, 2017). The rapid growth of product variety has significantly increased operational costs such as inventory and out-of-stock costs. What makes the matter more urgent is that for most of the grocery stores, the shelf space does not grow concomitantly with increasing product variety.

Because growth in total product variety spikes operating costs and increases the possibility of stock-outs, which ultimately hurts retailers' profits (Alfaro & Corbett, 2003; Fisher & Ittner, 1999; Shockley et al., 2015; Ton & Raman, 2010). This is especially a concern for stores that have tighter space constraints, such as stores located in urban areas and convenience stores. In addition, such capacity constraints have become more prominent because of shrinking store sizes: on average, newly opened stores are about 25 percent smaller than existing stores (McKinsey & Company, 2013). Therefore, it is challenging for retailers to choose the correct organic and conventional product mix when increasing their organic product offerings. Although how organic assortment, price, and promotions drive retailer performance has been studied in previous work, an in-depth understanding of how consumers make complex purchase decisions involving organic products among numerous other non-organic related attributes is missing. In this study, we seek to find how consumers would make their purchase decisions when facing such complex choices and what is the best assortment mix for retailers that carry both organic products and conventional products.

We examine the following research questions: *(1) How consumers evaluate organic products when there are multiple features and attributes of the organic product, and directly evaluate the cannibalization effect of conventional products on organic products. (2) What is the best assortment mix for retailers who sell both organic and conventional products?* Specifically, we examine the relative effect of product attributes (price, brand, nutrition information, style, etc.) and seller-related attributes (store type, store size, promotion, advertising, etc.) on consumers' choices for organic products. We focus our study on sales of yogurts for several reasons. First of all, both organic yogurts and conventional yogurts experience rapid growth in both sales and the richness of product features. The strong performance in yogurt industry leads to an explosion of product variety, therefore retailers must carefully choose the products to carry on the shelf. Second, unlike most of the packaged consumer goods, yogurts typically have a relatively short shelf life (about 3 weeks) and have to be stored in the refrigerated area. Therefore, anything that does not sell at the end of the shelf life would be a waste of both money and the precious shelf space. Third, yogurts are often on price promotions, and consumers are likely to purchase the products on sale. The increase of sales in promotional items and the decrease of sales in non-promotional items make retailers difficult to evaluate the effect of the promotions. Therefore, retailers need a better understanding of the substitutional effects on the products they carry.

We use four years (2008-2011) of weekly scanner data obtained from Information Resources Inc. (IRi) and employ structural estimation techniques developed in the empirical industrial organization literature to conduct our analysis (Berry 1994). This analysis method allows us to better understand why a consumer makes a particular choice and how the consumer analyzes trade-offs among the attributes of the choices.

Our research contributes to the operations management literature as follows. Although organic products have been perceived as having a better quality, taste, and healthier in terms of pesticide residue than its conventional counterparts, the direct competition between organic products and their conventional counterparts has received little attention. Our study builds on a recent stream of work exploring how price and marketing actions (Ngobo, 2011; Bezawada & Pauwels, 2013) influence consumers' attitudes and willingness to pay for organic products. However, most papers in this stream assume consumers face a simple binary choice: an organic product or a conventional product. They also assume consumers have no preference for all other choices within the same product category. In practice, however, consumers' preferences for organic products and conventional products may also be influenced by product brand, style, and other attributes. Additionally, consumers may choose where to shop such as a bigger retailer or a small convenience store. Overall, our study includes a much broader choice set than those represented in previous studies. And we also account for consumers may have a certain preference for what types or brands of products they would like. By analyzing the relative effects of the noted product and seller-related variables on consumers' choices, we extend the previous literature by conducting a more direct examination of the cannibalization effect between organic products and conventional products.

3.2. Literature Review

In this section, we review the literature from two related streams of research: what are the key factors for consumers to choose from organic or conventional products and choice modeling techniques in operations management literature.

3.2.1 How Consumers Choose Between Organic and Conventional Products

Organic product sales have increased from \$3.6 billion in 1997 to \$47 billion in 2016 (Organic Trade Association, 2016). Consumers value organic food because it is seen as being healthier, more nutritious, better tasting, and safer because no chemicals are used in its production (Bauer et al., 2013). According to anecdotal evidence, consumers often purchase organic produce according to the "dirty dozen and clean fifteen" standards, which identify groceries with the most pesticide residue and those with the least contamination (Pou, 2010). Currently, consumers in the United States buy more organic products in traditional supermarkets than in other outlets . Meanwhile, traditional supermarkets are increasingly promoting organic products through various in-store marketing programs (e.g., increasing variety, displays). Because organics have higher gross margins, 30% to 50% versus 20% to 25% for conventional products (Oberholtzer et al., 2006), promoting organic products would enhance total category profits and store revenues (Bezawada & Pauwels, 2013).

The growing segment of organic consumers is usually associated with higher disposable income, higher education, and lower price sensitivity (Krystallis et al., 2006). More recent studies start to find that this growing segment of consumers does not exclusively buy organic: a 2009 study by the Hartman Group found that, while 21% of consumers buy organic only, 65% of consumers buy both conventional and organic products (Chait, 2017). Evidence shows that organic customers also purchase conventional products if they find them attractive, particularly when the prices of organic products are too high or when the supply of organic products is limited (Hudson, 2012). However, there has not been much study to investigate exactly how much does organic customers care about product price or promotions, and how do customers choose between the two broad product categories. Not to mention how do consumers choose among all the different products and facing much more complex choices than choosing only between organic and conventional products.

A handful of studies used revealed data (typically scanner panel) to analyze how organic consumers react to retail prices, and they have mixed findings. Glaser and Thompson (2000) report large own-price elasticity (between –3.63 and –9.73) for U.S.

organic milk in the late 1990s. They also find the cross-price elasticity suggests that organic and branded conventional milk are substitutes. However, the substitution response is asymmetry where change in organic milk has little effect on conventional branded milk whereas change in conventional branded milk has a great effect on organic milk. In contrast, Kiesel and Villas-Boas (2007) report small price elasticity (between –.001 and –.003) for U.S. organic milk in the 2000s. By study data from Europe, Ngobo (2011) concludes that organic products may be a poor fit for traditional marketing actions such as price reduction and a higher variety. However, using United States data, Bezawada and Pauwels (2013) find that enduring actions, such as assortment and regular price changes, have a higher elasticity for organics than for conventional products. That is, in contrast with common wisdom, even "core" organic consumers are sensitive to these actions.

The extant literature does not, however, provide a clear understanding of how other product-related (style, brand, nutrition, etc.) and seller-related factors influence consumers' preferences when choosing between organic products and conventional products. In addition, all of the studies mentioned above do not assume consumers may have a certain preference for how they choose to buy their products. In practice, however, consumers may first select a style than select whether to buy an organic product within that style, or they may first decide whether to buy an organic product or a conventional one than select a style later. Our study accounts for such consumer preferences by using conditional nested models, therefore, we help fill this gap in the literature by using revealed purchase data to calculate cross-price elasticities between product organic status and styles.

3.2.2. Choice Modeling Techniques in Operations Management Literature

Capturing and understanding consumer choice behavior has become more and more important to business managers (Garrow 2016). As the increase in product options in retail markets has significantly expanded the number of options that are available to consumers (Ton & Raman, 2010). Choice models, which allow researchers to understand how a consumer evaluates the attributes of alternatives within a product category, are one approach to studying consumer choices. The discrete-choice demand model stemming from McFadden (1978) and Manski and McFadden's (1981) random utility framework is a widely-leveraged approach to understand consumer choices. The discrete-choice demand model was intended to provide an appropriate framework for the empirical analysis of choice among finite sets of alternatives, with each alternative characterized as a bundle of attributes (Manski, 2001). McFadden (1978) supposed that each member of a population of interest faces a finite choice set and selects an alternative that maximizes his/her utility. Further, the model assumes that the purchase decisions of consumers are affected by the selection of products that a seller offers. In the field of operations management, choice modeling techniques have been used in a wide range of research contexts. In retail operations, for example, researchers have used these methods to assist with assortment planning (Rusmevichientong et al., 2010; Kok and Xu 2011; Li and Huh, 2011; Rusmevichientong & Topaloglu, 2012). To perform our analyses, we leverage the structural estimation technique introduced by Berry (1994) which allows for the development of models of demand and supply equations. The Berry (1994) and Berry et al., (1995) models were one of the first methods to estimate demand based on random utility maximization (RUM) models, using aggregate market-level sales data. In the recent Operations literature, the Berry structural estimation model has been employed by Nevo (2001) to estimate the price margin in the ready-to-eat cereal industry, Allon et al., (2011) to estimate the value of reducing customer wait times in the drive-thru fast-food industry, Guajardo et al., (2016) to examine how various product and service attributes affect demand for US automobiles and McKie et al., (2018) to examine how consumers' choices for different generation and conditions of iPads are affected by seller and product attributes on eBay. Similarly, we leverage the model to understand how consumers' choices for organic and conventional yogurts are affected by market and product-related variables.

The Berry model distinctively assumes prices are endogenously determined by firms., while most of the existing empirical literature on this topic assumes prices are exogenous. The exogenous assumption has been noted as a significant limitation in the literature (Berry 1994, Guajardo et al., 2016). Therefore, we follow Guajardo et al., (2016) and Mckie et al., (2018), to develop instrumental variables for the price and nested market share, using the sum of the other observations' characteristics (see section 3.4.2). Thus, similar to Guajardo et al., (2016) and McKie et al., (2018), from a methodological perspective we extend the previous research on this topic through directly controlling for the endogeneity of prices.

3.3. Data and Measures

We first describe our data source and sample size in Section 3.3.1, and then we describe the dependent, independent, and control variables used in our analyses in Section 3.3.2.

3.3.1. DATA

We use four years of proprietary scanner data (2008-2011) from IRi, which reports data for grocery chains and drug stores in 50 markets in the U.S. (except Alaska and Hawaii). The raw data contains three files that separately report: 1) weekly Stock Keeping Unit (SKU) sales and unit price, 2) SKU attributes (e.g., product type, organic status, fat content, promotion, and product size), and 3) store information (location, chain affiliates, market, and store's annual sales). An SKU is defined as a unique combination of brand, flavor, weight, container material, container size, and pack size. We first use the Universal Product Code (UPC) number to identify each SKU and then combine the SKU sales data with the SKU attributes data. We then use the store ID from both the SKU sales data and store information data to arrive at our final sample. We use data pertaining to the yogurt category to test our hypotheses for two main reasons. First of all, both organic yogurts and conventional yogurts experience rapid growth in both sales and the richness of product features. The strong performance in yogurt industry leads to an explosion of product variety, therefore retailers need to carefully choose the products to carry on shelf. For example, in our sample, the total number of varieties of yogurt in the US market soared 32% from 4,581 in 2008 to 6,053 in 2011. In comparison, the organic SKU category increased 30%, from 256 SKUs (in 2008) to 331 SKUs (in 2011). Moreover, we also see large number of SKUs in almost every yogurt type and style. The richness in yogurt variety enables us to better understand consumers' specific preferences in certain product attributes. Second, unlike most of the packaged consumer goods, yogurts typically have a relatively short shelf life (about 3 weeks) and have to be stored in the refrigerated area. Therefore, anything that does not sell at the end of the shelf life would be a waste of both money and the precious shelf space. Third, yogurts are often on price promotions, and consumers are likely to purchase the ones on sale. The increase of sales in promotional items and the decrease of sales in non-promotional items make retailers difficult to evaluate the effect of the promotions. Therefore, retailers need better understanding of the substitutional effects on different products they carry. The yogurt category in the raw data has 7,112 SKUs in total, including discontinued SKUs and yogurt by-products, such as almond yogurt, buffalo milk yogurt, yogurt smoothies, and kefir. We dropped all yogurt by-products in our study to focus on the main yogurt category products. Our final sample is an unbalanced panel dataset that contains 208 weeks of data for 1,896 stores in 50 markets. Two kinds of stores are included in our dataset: grocery stores and drug/convenience stores. There are 1,561 grocery stores and 335 drug/convenience stores in our final sample. Our dataset does not contain wholesale clubs such as Costco and Sam's Club. Across all the stores, there are 6,053 yogurt SKUs, including 242 brands produced by 88 manufacturers (including private-labels). To address our research questions, we aggregated the raw data at the weekly store level, that is, we calculated the total sales of each SKU in a store i at week t. We also calculated other store-specific characteristics based on sales data, as described below.

3.3.2. Product and Transaction-Related Variables

We extracted all product and transaction-related information from the final data sample. We use the UPC code as the identification of each SKU, and extract all product-related information from the sales data at store-week level.

3.3.2.1. PRICE

Price is one of the most important factors when consumers make purchase decisions. In our research settings, different yogurts have different prices and are in different package sizes. To standardize the price on each product, we follow Nevo (2001) to convert all product prices to Dollars per Pint.

3.3.2.2. ORGANIC

For each SKU, there is a binary variable indicates whether the product is organic. We thus model Organic as a binary variable that equals 1 if the SKU is an organic product, and 0 if the SKU is a conventional product.

3.3.2.3. STYLE

Amongst our SKU level weekly sales of 52,329,765 observations, We observe 31 different styles in our dataset, including the most commonly observed yogurt styles such as Grade-A (32,300,000 observations), Greek (4,155,480 observations), Creamy (2,691,613 observations), All-Natural (2,336,685 observations), and some less commonly seen styles such as Bulgarian (2,493 observations), Kosher (335 observations). We also have some observations that marked style as Missing (408,631 observations). Note that the Grade-A yogurt style in our dataset stands for yogurts that do not specifically have a style (e.g. Yoplait Original, Dannon Activia, Stonyfield Farm, etc.), because according to USDA regulations, all yogurts made and sold in the united states must be made from Grade-A milk. As a result, we renamed the Grade-A yogurt style as "Regular". And because there are no other styles of yogurt (except Greek, All-Natural, Creamy, and Regular) have more than 1,000,000 observations in our data, we combined all other styles including Missing and rename them as "Other" style. We thus model Style as a categorical variable that equals 1 if the product style is Greek, 2 if the product style is All-Natural, 3 if the product style is Creamy, 4 if the product style is Regular, and 5 if the product style is Other.

3.3.2.4. Private-label

For each SKU, we also find if the product if a private-label product. We leverage this information because consumers may have a different preference for private-label products, and private-label products directly compete with national brand products (Ailawadi & Keller, 2004). We model Private-label as a binary variable that equals 1 if the product is a private-label product, and 0 if the product is a national brand.

3.3.2.5. Brand

There are 232 different brands in our dataset. As a product brand is apparently a key factor in consumers' choices (Macdonald & Sharp, 2000), we model brand as a categorical variable that represents each different brand names.

3.3.2.6. Fat-Content

We also acquire the fat-content information for each product in our dataset because fat-content is another key factor that affects consumer choices in the dairy product category. There are 21 different levels of fat-content in our data. And this high variability is due to different brand describe their fat-content in different ways. For example, some brands describe their product as "1% Low Fat" whereas some other brands describe their product as "99% Fat-Free". We leverage the fat-content information and create a categorical variable FatContent, that equals 1 to 21 to identify the fat-content on each product.

3.3.3. Seller related variables

There are 1896 unique sellers (stores) in our dataset. We extract several store attributes that may affect consumer choices when they shop at the stores.

TotalVatirety measures the total number of yogurt SKUs that were sold in the store *i* at week *t*. As indicated in the operations literature, higher variety often leads to higher sales because consumers are more likely to find the product they needed (Bayus & Putsis, 1999; Xia & Rajagopalan, 2009; Ton & Raman, 2010).

PackageSize measures the average size of the yogurt products in the store *i* at week *t*. Larger stores typically have higher average product sizes, and they carry more product variety at a lower price than smaller stores (e.g., big-box retailers compared to small convenience stores), therefore consumers are more likely to find the product they needed and make purchases.

Advertisement measures the percentage of yogurt in the store that is on store advertisement. Although advertisement may be an effective way to increase consumer purchases on the advertised products, it may also reduce consumer purchases on products that are not on advertisement.

Discount measures the percentage of yogurt in the store *i* that is on sale at week *t*. Similar to *Advertisement*, a high percentage of discounted items may increase sales on the discounted items, but reduce the purchase of products that are not on sale.

In addition, the 1896 stores belong to 103 retail chains that reside in 50 metropolitan markets in the United States. Although the retail chain names are masked, we can still identify and tie each store to its retail chain in a certain market area.

3.3.4. Aggregation Technique and Descriptive Statistics

To prepare the data for analysis, we first segment the transactions by week and market. Specifically, we define 10400 (208 weeks * 50 markets) markets by geographic conditions and week indicators as in the dataset. Because both time and geographic conditions limit the options that a consumer faces when purchasing from a brick and mortar store. In addition, segmenting markets by time also captures factors like seasonality. The total sales figures were calculated from the dataset by adding up all yogurt sales in each market. We aggregated the data in each market by seller *i*. Thus, for each week and market, we calculated the average values for each seller (*i*) that sells brand (*j*), style (*k*), organic (*l*) private-label (*m*), and fat content (*n*).

Descriptive statistics for yogurt types and styles are presented in table 3.1 to table 3.3. We also present descriptive statistics for relevant categorical and continuous variables, and related correlation tables in table 3.4 to 3.6, respectively.

Table 3.1 Descriptive Statistics for Yogurt Organic Condition

Type	Observations	Mean Price	SD
Conventional	47,673,234	1.5394643	1.309206
Organic	4,656,531	2.3719485	1.411112

Table 3.2 Descriptive Statistics for Yogurt Styles

Style	Observations	Mean Price	SD
Greek	4,155,480	2.0869939	1.394539
All-Natural	2,336,685	1.5532751	1.055484
Regular	37,369,292	1.5760708	1.351474
Creamy	4,620,210	1.6390927	1.351839
Other	3,848,098	1.4720824	1.192319

Table 3.3 Descriptive Statistics for Yogurt Style-Organic

Style-Organic	Observations	Mean Price	SD
Greek C	3,669,098	2.025438	1.396479
Greek O	486,382	2.5513501	1.288286
All-Natural C	2,102,488	1.6220092	1.089219
All-Natural O	234,197	0.93621957	0.203318
Regular C	35,791,981	1.5470951	1.343409
Regular O	1,577,311	2.2335811	1.366869
Creamy C	3,061,037	1.1779839	1.011411
Creamy O	1,559,173	2.5443619	1.47309
Other C	3,048,630	1.1710205	0.93052
Other O	799,468	2.6201287	1.370132

Table 3.4 Descriptive Statistics for Categorical Variables

Variable	Catagories	Count	Percentage
Organic	0: Conventional	47,673,234	91.10%
	1: Organic	4,656,531	8.90%
PrivateLabel	0: National Brand	43,868,510	83.83%
	1: Private-label	8,461,255	16.17%
Style	1: Greek	4,155,480	7.94%
	2: All-Natural	2,336,685	4.47%
	3: Regular	37369292	71.41%
	4: Creamy	4,620,210	8.83%
	5: Other	3,848,098	7.35%

*Note*s. Brand and Fat Content are omitted for abbreviation.

Table 3.5 Descriptive Statistics for Continuous Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Price	52,329,765	2.082268	0.8962213	0.005	159.98
PackageSize	52,329,765	0.7997985	0.0864905	0.25	2
Advertisement	52,329,765	0.1346979	0.1074949	0	1
TotalVariety	52,329,765	213.6298	63.39978	1	503
Discount	52,329,765	0.2641606	0.1493009	0	1
StoreRevenue	52,329,765	29.69415	17.27097	0.11	146.241

Table 3.6 Correlation Table

	Price	*Package Size*	*Advertisement*	*Total Variety*	*Discount*	*StoreRevenue*	*Organic*	*PrivateLabel*	*Style*
Price	1								
PackageSize	-0.1005*	1							
Advertisement	-0.0198*	-0.0299*	1						
TotalVariety	0.1272*	-0.1312*	-0.0065*	1					
Discount	-0.0478*	0.0786*	0.4566*	-0.0296*	1				
StoreRevenue	-0.0039*	0.0877*	-0.0700*	0.5183*	-0.1390*	1			
Organic	0.2333*	-0.0316*	-0.0043*	0.1094*	-0.0267*	0.0949*	1		
PrivateLabel	-0.3675*	0.1119*	0.0154*	-0.0904*	0.0197*	-0.0100*	-0.0466*	1	
Style	-0.3421*	-0.0054*	0.0061*	-0.0567*	0.0005*	0.0043*	0.1403*	0.0517*	1

Notes. * denotes significance at $p < .05$ level.

3.4. Analysis and Initial Results

3.4.1. Analysis

Choice modeling is the most natural approach for determining how consumers choose between different product attributes (i.e., organic or conventional) of the same product (Garrow, 2016). However, in our research setting, a direct application of choice models (such as multinomial or nested logit) is difficult as we do not know what other options each consumer was exposed to when they made their purchase decision. We leverage the Berry (1994) method for demand estimation in differentiated markets, where we could use aggregate sales data to estimate the impact of price and other product and seller characteristics on product demand. To develop the model, we first define the utility of an individual *i* purchasing product *j* as

$$U_{ij} = \alpha p_j + \beta x_j' + \xi_j + \epsilon_{ij} \tag{3.1}$$

where p_j is the average price of product j, x_j' is a vector of product and seller characteristics (i.e., total variety, store revenue, discount level) observed by both researchers and consumers, ξ_j is a vector of characteristics (i.e., product, environmental, demographic, etc.) unobserved by the researchers but observed by consumers, and ϵ_{ij} is an error term representing consumer i's idiosyncratic preferences for product j. We express the aggregate utility for product j as

$$\delta_j = \alpha p_j + \beta x_j' + \xi_j \tag{3.2}$$

Using Berry's (1994) inversion method, we derive the following non-nested model

$$ln(s_j) - ln(s_0) = \delta_j = \alpha p_j + \beta x_j' + \xi_j \tag{3.3}$$

where s_j is the market share of product *j* and s_0 is the market share of the outside option.

The outside option in the Berry (1994) formulation represents the market share of any alternative product that a customer is presented and considered when choosing whether or not to purchase an available product from the retailer. There are several choices that we could choose for the outside option parameter. A more conservative choice is to assume that consumers only consider yogurts offered through the current store they are shopping at. In this case, the total sales of yogurt sold in the same store are used as the reference. However, this option omits the activity of shop-hopping, which is widely observed in consumer behavior (Steiner, 1984). Therefore, we leverage a less conservative choice, that is to assume that customers consider purchasing yogurts from all stores within a market, including the stores that are not included in our dataset. In this case, the total sales of all yogurts in the same market would be used. Specifically, we compute s_0 as the ratio of total sales of other yogurts on the market that is not observed in our dataset (i.e., the outside option) against the total sales of yogurt on the same market (including the sales observed in our dataset) during the same time period as our study.

The above described non-nested model violates the property of the independence of irrelevant alternatives. Specifically, consumers usually have preferences for product brand, style, etc. In other words, a consumer who purchases a Stonyfield yogurt may be more likely to select another Stonyfield yogurt than a Yoplait when their first choice is not available. *A priori*, we do not know what the best nesting structure is. It may be that customers are more likely to purchase within the same brand, or they may be more likely to purchase within the same organic condition. Thus, we build several models where we next our data by Brand, Organic, Style, etc. We finally choose to nest our data by Brand and Organic, as suggested in previous literature, consumers recognize both brand and organic label as the most important factors of their purchase intention (Konuk, 2018;

Bauer et. al., 2013). Therefore, we assume consumers are more likely to purchase within the same brand and organic condition when their first choice is not available.

We created 233 nests (g=0, 1, 2, …, 232) based on Brand-Organic pairs, where each number indicates a different combination of brand and organic attributes, and g=0 represents the outside option only. Using the Berry inversion method, we derive the nested logit model as

$$ln(s_j) - ln(s_0) = \alpha p_j + \beta x_j' + \sigma\, ln(s_{j|g}) + \xi_j \quad (3.4)$$

where σ is the factor measuring substitutability ($0 < \sigma < 1$) and $s_{j|g}$ is the market share of product *j* in nest *g*.

3.4.2. Condition Nested Model

Table 3.7 presents the 2-stage lease square (2SLS) estimates of our condition nested model. As can be seen in the table, we find that *price* has a negative (β=-0.73) and highly significant ($p < .001$) effect on consumers' choices. Further, the estimate of the coefficient *r* of nested market share is 0.66, which falls in the acceptable range between 0 and 1, indicating that it captures substitutability (Berry 1994). Finally, the coefficients of *PrivateLabel* is positive and significant, that is, all else equal (including price), demand is higher for a private-label product.

Table 3.7: Condition Nested Model, IV Estimates

DV($ln(s_j) - ln(s_0)$)	*Coef.*	*Std. Err.*	*z*	*P>z*	*[95% Conf.*	*Interval]*
Price	-0.73354***	0.008777	-83.57	0	-0.7507502	-0.716343
Ln($S_{j\|g}$)	0.665793***	0.000441	1506.97	0	0.664927	0.6666589
PackageSize	0.603629***	0.005102	118.3	0	0.5936282	0.6136305
Advertisement	-0.23797***	0.002423	-98.2	0	-0.2427265	-0.233226
PrivateLabel	0.758617***	0.006222	121.91	0	0.7464212	0.7708139
StoreRevenue	0.004215***	0.000039	106.13	0	0.0041381	0.0042938
Discount	0.939448***	0.002602	361.02	0	0.9343486	0.9445489
TotalVariety	0.001263***	7.67E-06	164.6	0	0.001248	0.0012781

Notes: * p < .10, ** p < .05, *** p < .01.

We use 2SLS estimates because it is likely that the product's price and nested market share are correlated with unobserved characteristics. For example, if there are unobserved factors (to the researcher) that may cause the demand for a particular brand or style to be higher in a certain period, then a seller may set a higher price (by not putting up a discount or promotion) for these products during that period. To correct for this possible endogeneity, we used instrumental variables (IVs) for price and nested market share. Specifically, the sum of the other products' characteristics (i.e., package size, advertisement level, and fat content) within a nest in a market was used as instruments for each observation's price and nested market share. The sum of the other observations' characteristics are appropriate instruments since they are excluded from the utility equation (U_{ij} or δ_j does not depend on product/seller characteristics of other observations) and they are correlated with prices via the markups in the first-order conditions (Berry, 1994; Berry et al., 1995). A similar set of instruments have been used in past operations management studies that have used aggregate choice models (e.g., Guajardo et al., 2016; McKie et al., 2018). We then tested endogeneity using both Durbin-Wu-Hausman Chi-squared and Wu-Hausman F scores. The Durbin Chi-squared statistic of 66024.6 ($p <$ .001) and Wu-Hausman F score 33063.8 ($p < .001$). In the first stage of 2SLS, we evaluated the explanatory power of our IVs by using the tests for excluded instruments for both price and nested market share. The null hypothesis that the excluded instruments have no explanatory power was rejected (Staiger & Stock 1997). Specifically, the F-statistics (p-value) for price and nested market share were 73524 ($p < .001$) and 780000 ($p < .001$), respectively. Second, we ran the test of underidentification of instruments. The null hypothesis that our instruments are underidentified was also rejected. Specifically, the Anderson Canonical Correlation LM Statistic is 82000 ($p < .001$). In sum, these tests provide validity to our model specification and the use of instruments to address the endogeneity of price and the nested market share variables (Guajardo et al., 2016; McKie et al., 2018).

3.5. Discussion of Main Results

Using the estimates in table 3.1 and Equation 5, we compute the product's own and cross-price elasticities using yogurt styles and/or organic as nests due to our research interests. For example, in table 3, for the own-price elasticities, we estimate whether the own-price elasticities of product style k (k = 2, 3, 4, 5) are different than the own-price elasticity of product style 1 (Greek yogurt) at the 95% significance level. Following McKie et al., (2018), we use the upper and lower confidence interval estimates of α and σ to estimate our significance level by checking to see if the elasticity estimates (calculated using either the upper or lower values from the 95% confidence intervals) have any overlaps. We estimate whether the cross-price elasticities of product pair (i, j) [$i \neq j$, $(i,j) \neq (2,1)$] are different from the cross-price elasticity of product type pair (2, 1) at the

95% significance level using the upper and lower confidence interval estimates of α and σ. As a result, the own-price elasticity shows the resulting percent decrease in market share when the price of a yogurt type increases by 1%. And the cross-price elasticity shows the resulting percent increase in market share when the price of another yogurt type increases by 1%.

$$\frac{\partial s_i p_j}{\partial p_j s_i} = \begin{cases} \alpha p_i[\frac{1}{1-\sigma} - \left(\frac{\sigma}{1-\sigma}\right) s_{i|k}] - \alpha p_i s_i\,, & if\ i = j \\ -\alpha p_j[(\frac{\sigma}{1-\sigma}) s_{j|k} + s_j]\,, & if\ i \neq j, i \in k, j \notin k \\ -\alpha p_j s_j, & if\ i \neq j, i, j \in k \end{cases} \tag{3.5}$$

3.5.1. OWN AND CROSS-PRICE ELASTICITY CALCULATIONS BY ORGANIC

We first report the own and cross-price elasticity by the organic condition in table 3.8. The diagonal represents the average own-price elasticities for organic and conventional yogurts. The own-price elasticity values show the resulting percent decrease in market share when the price of a yogurt increases by 1%. For example, 1% increase in conventional yogurt prices in a store would result in on average 4.39% decrease in market share for that store. Similarly, 1% increase in organic yogurt price in a store would result in on average 5.95% decrease in market share for that store. The off-diagonal represents the average cross-price elasticity values for organic and conventional yogurts. The cross-price elasticity values show how price changes in the conditions listed in the columns affect market share for the conditions listed in the table rows. For example, 1% increase in conventional yogurt prices in a store would on average increase the market share of organic yogurt for that seller by 0.026%. Similarly, 1% increase in organic yogurt price in a store would on average increase the market share of conventional yogurt for that seller by 0.089%.

Table 3.8: Own and Cross-price Elasticity by Organic

	Conventional	*Organic*
Conventional	-4.39664	0.08900
Organic	0.02647†	-5.95207*

Notes: *Denotes own-price elasticity of product type j (j = 2) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) [$i \neq j, (i,j) \neq (2,1)$] is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

We find that the own-price elasticity for organic yogurt is significantly greater than that of conventional yogurt (-5.95 versus -4.39). This finding is consistent with previous literature -- Bezawada and Pauwels (2013), that suggests even core organic consumers are price sensitive. A possible explanation for this result is that consumers are more price-sensitive to products that are more standardized in nature (McKie et al., 2018). Where organic products have much more standardized requirements in their production process, conventional products do not have strict requirements regarding the raw materials, manufacturing processes and transportation processes. The results also suggest that although consumers are generally willing to pay higher prices for organic products, the high price sensitivity may off-set the benefit of higher pricing if retailers are not aware of such market effects.

The cross-price elasticity suggests that although conventional and organic products are substitutes, the substitution effect is asymmetry. Our results allow us to evaluate the cannibalization effect of conventional products to organic products. We find that change in organic price has a greater effect on conventional yogurt (0.089) whereas change in conventional price has a smaller effect on organic yogurt (0.026). Contrast to Glaser and Thompson (2000), who finds that changes in conventional milk prices have a greater effect on organic milk. The different findings may stream from model specification, where Glaser and Thompson (2000) used only half-gallon packaged milk data and ignored the possible substitution between different package sizes. In reality, it is possible that consumers would buy a larger package size to retain low average price (e.g. price per gallon) when they see a price increase in half-gallon milk. It is also possible that consumers would switch to a lower package sized milk to retain total costs. Failing to capture such phenomenon may lead to bias in estimating cross-price elasticity. Another possible explanation for this phenomenon is that the overall product variety for organic yogurt is much smaller than the product variety for conventional yogurt. Therefore, it is more difficult for consumers to find a substitution product with similar taste, style, fat-content in organic form when consumers' first choice is a conventional product. On the contrary, it is easier for consumers to find a close substitute in the conventional form when consumers' first choice is an organic product.

3.5.2 Own and Cross-Price Elasticity Calculations By Style

Table 3.9 shows the own and cross-price elasticity by yogurt styles. From the own-price elasticity results, we find that Greek yogurt is the most sensitive to price change. With 1% price increase in Greek yogurt, the market share of Greek yogurt would decrease on average 8.62%, followed by Other (5.07%), Creamy (4.29%), All-Natural (4.17%), and Regular (4.07%). Further, there are significant differences in own-price elasticity among different yogurt styles. For example, as we could see above, the own-price elasticities for All-Natural yogurt, Regular yogurt, and Creamy yogurt are much lower than Greek yogurt.

Table 3.9: Own and Cross-price Elasticity by Style

Style	*Greek*	*All-Natural*	*Regular*	*Creamy*	*Other*
Greek	-8.62977	0.03127†	0.02673†	0.03896	0.04766†
All-Natural	0.03855	-4.17157*	0.02239†	0.02045†	0.03141†
Regular	0.05328†	0.03401†	-4.07611*	0.03527†	0.04834†
Creamy	0.04718†	0.02087†	0.02356†	-4.29577*	0.03744
Other	0.04775†	0.02255†	0.02468†	0.02775†	-5.07809*

Notes: *Denotes own-price elasticity of product type j (j = 2, 3, 4, 5) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) [$i \neq j, (i, j) \neq (2,1)$] is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

One possible explanation for this result is that own-price elasticity could be decreasing by the average price for each product style. Because in our model specification, own-price elasticity is a function of the product's price. However, although Greek yogurt does have the highest average price and highest own-price elasticity, the other four product styles do not fall into the rule of "the higher price, the higher own-price elasticity". For example, the average price for Greek yogurt is 2.08 dollars per pint, followed by Creamy (1.63), Regular (1.57), All-Natural (1.55), and Other (1.47). Thus, it is feasible that our results do indicate differences in consumers' sensitivity to product style, as the own-price elasticity is not just a reflection of price.

Another possible explanation for the own-price elasticity difference is that consumers may find it easier to find a close substitute in styles that have more product variety than those that have less product variety. In our dataset, we have 333 SKUs in Greek yogurt, where we have 148 SKUs in All-Natural yogurt, 2469 SKUs in Regular yogurt, 193 SKUs in Creamy yogurt, and 715 SKUs in Other yogurt. Therefore, although Greek yogurt has a lower number of SKU than Regular and Other yogurt, it actually has more SKUs than All-Natural yogurt and Creamy yogurt. Therefore, we believe that the own-price elasticity is not driven by the availability of substitutes in the same category. Rather, our results do indicate that consumers are more sensitive to price changes in certain styles. In addition, this additional own-price elasticity in Greek yogurt indicates that although it is believed that people are willing to pay a bit more for Greek yogurt because it is healthier, the high price sensitivity may off-set the benefit of higher selling price if the retailer is not aware of such market effect.

From the cross-price elasticity values, we find that different styles of yogurts are substitutes, as all cross-price elasticity estimations are positive. Next, we find gains in market share of the other four styles are higher when the price of Greek yogurt increase as compared to similar increases in the price of the other four styles. This result may suggest that regular consumers for Greek yogurt have a higher disposable income (Boynton & Novakovic, 2014; Mohammed et al., 2018). This substitution effect is also asymmetric, as when Greek yogurt increase 1% in price, the market share of All-Natural yogurt, Regular yogurt and Creamy yogurt would increase market share by on average 0.038%, 0.053% and 0.047% respectively. Whereas when All-Natural yogurt, Regular yogurt and Creamy yogurt increases 1% in price, the market share of Greek yogurt would only increase 0.031%, 0.026% and 0.038% respectively.

We find Regular yogurt seems to be the most possible substitute for all other yogurt styles except for Creamy yogurt. When Greek yogurt, All-Natural yogurt, and Other yogurt increases 1% in price, the Regular yogurt has the most growth in market share (0.053%, 0.034% and 0.048% respectively). However, for Creamy yogurt, the Greek yogurt is the closest substitute, as 1% increase in Creamy yogurt price would increase

Greek yogurt market share by 0.038%. This is likely resulting from the similar texture and taste between the two styles.

3.5.3 Own and Cross-Price Elasticity Calculations By Style and Organic

Table 3.10 shows the own and cross-price elasticity by both yogurt styles and organic conditions. The results allow us to further understand (1) How consumers evaluate organic products when there are multiple other features and (2) What is the best assortment mix for retailers who sell both organic and conventional products.

From the own-price elasticity, we find that similar to own-price elasticity calculation in 3.5.1, organic products have a higher own-price elasticity in every yogurt style. Our findings further suggest that consumers do care about organic pricing. And retailers need to be aware of such market effect and avoid pricing organic products too high. Next, we find that Organic Greek yogurt has the highest own-price elasticity. 1% increase in Organic Greek yogurt price would result in 11.9% decrease in its market share. Although Organic Greek yogurt is one of the most expensive types of yogurt in our dataset (2.55 dollars per pint), which may play a role in its high own-price elasticity, other types of yogurt do not show a strong correlation between the average price and own-price elasticity. In fact, the Conventional Greek yogurt has an average price of 2.02 dollars per pint, which is cheaper than Organic Regular (2.23 dollars per pint), Organic Creamy (2.54 dollars per pint) and Organic Other yogurt (2.62 dollars per pint). Yet, the Conventional Greek yogurt has higher own-price elasticity than any organic yogurt listed above. Another explanation for the high own-price elasticity in Organic Greek yogurt is the lack of variety in this product category. Indeed, there are only 25 SKUs in this product category, offered by only 2 brands (Stonyfield Oikos and Voskos). However, the own-price elasticity is not just a reflection of product variability as Conventional Greek yogurt has 308 SKUs and is offered by 27 brands, while the Organic Regular yogurt has only 181 SKUs that are offered by similarly 31 brands. Thus, we believe that consumers do have different price sensitivity in Greek yogurt, as the own-price elasticity is not just a reflection of price or product variety. This finding in Greek yogurt further suggests retailers should beware of their Greek yogurt pricing, as consumers are the most price-sensitive in this product category.

From the cross-price elasticity, we are able to directly examine the effect of cannibalization from conventional products to different types of organic products. For Organic Greek yogurt, we find that when the price of Organic Greek yogurt increases by 1%, the yogurt types that gain the most market share are Conventional Creamy, Conventional All-Natural, and Organic All-Natural. A possible explanation for this result is that consumers for Greek yogurt are attracted by the texture of Creamy yogurt and the healthy massage carried by All-Natural yogurt. However, as these consumers are price-sensitive, they are less likely to purchase Organic Creamy yogurts which have very similar price to Greek yogurt. Further, the substitution among these groups is asymmetric. Where increase in Organic Greek yogurt price by 1% would result in more than 0.2% market share increase in Conventional Creamy, Conventional All-Natural and Organic All-Natural yogurt, 1% increase in Conventional Creamy, Conventional All-Natural and Organic All-Natural yogurt would only increase Organic Greek yogurt market share by 0.08%, 0.06% and 0.01% respectively.

Table 3.10: Own and Cross-price Elasticity by Style and Organic

	Greek C	*Greek O*	*All-Natural C*	*All-Natural O*	*Regular C*	*Regular O*	*Creamy C*	*Creamy O*	*Other C*	*Other O*
Greek C	-8.1942	0.1544†	0.06096†	0.00993†	0.02212†	0.15568†	0.0718†	0.04988	0.0705†	0.07861†
Greek O	0.0501	-11.915*	0.06232†	0.01090†	0.02307†	0.15993†	0.0840†	0.0447†	0.0817†	0.07773†
All-Natural C	0.0669†	0.2241†	-4.0267*	0.01080†	0.02123†	0.15192†	0.0669†	0.0367†	0.0804†	0.07422†
All-Natural O	0.0707†	0.2180†	0.05109	-5.4715*	0.02163†	0.14298†	0.0720†	0.0158†	0.0848†	0.06040†
Regular C	0.0478†	0.1788†	0.04151†	0.00732†	-4.0161*	0.14193†	0.0384†	0.0403†	0.04980	0.06655†
Regular O	0.0455†	0.1650†	0.04411†	0.00647†	0.01935†	-5.4376*	0.0449†	0.0334†	0.0551†	0.06151†
Creamy C	0.0664†	0.2313†	0.04916†	0.01064†	0.02037†	0.14666†	-4.013*	0.0364†	0.0693†	0.0736†
Creamy O	0.0474†	0.1552†	0.03862†	0.00053†	0.02065†	0.13044†	0.0448†	-4.849*	0.0541†	0.05125
Other C	0.0572†	0.1976†	0.05133†	0.01030†	0.02169†	0.15379†	0.0596†	0.0401†	-4.933*	0.0751†
Other O	0.0567†	0.1972†	0.04151†	0.00460†	0.01991†	0.13372†	0.0477†	0.0258†	0.0591†	-5.630*

Notes: *Denotes own-price elasticity of product type j (j = 2, 3, 4, 5, 6 ,7 ,8 ,9 ,10) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) $[i \neq j, (i, j) \neq (2,1)]$ is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

With regard to Organic All-Natural yogurt, this product category has the lowest cross-price elasticity among all product types. 1% increase in Organic All-Natural yogurt price would result in 0.01% or lower market share increase in all other product categories. This result may be driven by the fact that all Organic All-Natural yogurt are supplied by Stonyfield Farm brand, and has an exceptionally low average price per pint (0.93 dollars). In fact, the average price for Organic All-Natural yogurt is the lowest among all 10 product categories. However, the Organic All-Natural yogurt is rarely the first choice when people substitute from other product categories (only exception is when Conventional Other yogurt price increases). Our finding suggests that the abnormally low price in organic products may raise concerns from consumers which would ultimately hurt the sales.

As for Organic Regular yogurt, it has relatively high cross-price elasticity in all product categories. That is, 1% price increase in Organic Regular yogurt would increase the market share of all other product categories by around 0.15%. Our findings suggest that competition between Conventional Regular yogurt and Organic Regular yogurt does exist. However, Organic Regular yogurt is much more vulnerable in this competition, as 1% price increase in Organic Regular yogurt would increase Conventional Regular yogurt market share by 0.14%, while 1% price increase in Conventional Regular yogurt would merely increase Organic Regular yogurt market share by 0.01%.

3.6. Robustness Check

One possible problem in our research is that we used 4 years of weekly data from the year 2008 to 2011. Whereat the beginning of this time period, Greek yogurt was very new to the market, therefore, creates a potential bias in the own and cross-price elasticity.

Therefore, we re-estimate our models using only the last 8 weeks of our data, where at the end of year 2011, Greek yogurt has become very mature on the market. We present our results in table 3.11 to table 3.13, where own and cross-price elasticity are calculated by organic, style, and organic-style accordingly.

Our results show that all previous findings are consistent. Moreover, the own-price elasticity for Organic yogurt and Greek yogurt is higher than the full sample estimation. Our results further validate that organic consumers indeed are price sensitive.

Table 3.11: Robustness Check: Last 8 Weeks Own and Cross-price Elasticity by Organic

	Conventional	*Organic*
Conventional	-6.63356	0.10677†
Organic	0.03026	-8.35953*

Notes: *Denotes own-price elasticity of product type j (j = 2) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) [$i \neq j, (i,j) \neq (2,1)$] is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

Table 3.12: Robustness Check: Last 8 Weeks Own and Cross-price Elasticity by Style

Style	*Greek*	*All-Natural*	*Regular*	*Creamy*	*Other*
Greek	-10.33744	0.05260†	0.02775†	0.05160†	0.05852†
All-Natural	0.04616	-5.611529*	0.02868†	0.04987†	0.05983†
Regular	0.04807†	0.05505†	-5.64319*	0.05443†	0.06053†
Creamy	0.04702	0.05038†	0.02904†	-5.95301*	0.05747†
Other	0.04914†	0.05321†	0.02953†	0.05251†	-7.68047*

Notes: *Denotes own-price elasticity of product type j (j = 2, 3, 4, 5) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) [$i \neq j, (i,j) \neq (2,1)$] is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

Table 3.13: Robustness Check: Last 8 Weeks Own and Cross-price Elasticity by Style and Organic

	Greek C	*Greek O*	*All-Natural C*	*All-Natural O*	*Regular C*	*Regular O*	*Creamy C*	*Creamy O*	*Other C*	*Other O*
Greek C	-9.9969	0.1536†	0.06452†	0.01079†	0.02246†	0.15843†	0.0766†	0.05264†	0.07213†	0.08347†
Greek O	0.0499	-15.968*	0.06808†	0.01227†	0.02390†	0.16585†	0.0940†	0.04914	0.08530†	0.08697†
All-Natural C	0.0628†	0.2019†	-5.4749*	0.01532†	0.02784†	0.19481†	0.1159†	0.06240†	0.11706†	0.11528†
All-Natural O	0.0689†	0.2028†	0.07560†	-7.4244*	0.03054†	0.18668†	0.1229†	0.03352†	0.12427†	0.11123†
Regular C	0.0435†	0.1496†	0.06193†	0.00875†	-5.5694*	0.16382†	0.0633†	0.05609†	0.06316†	0.08324†
Regular O	0.0416†	0.14211†	0.06282†	0.00780†	0.02227†	-7.2848*	0.0752†	0.04223†	0.07027†	0.07586†
Creamy C	0.0598†	0.1984†	0.07415†	0.01483†	0.02730†	0.19140†	-5.518*	0.06002†	0.10976†	0.11155†
Creamy O	0.0439†	0.1322†	0.06173†	0.00083†	0.02316†	0.14326†	0.0769†	-6.471*	0.06777†	0.07314†
Other C	0.0532†	0.1752†	0.07110†	0.01339†	0.02562†	0.17909†	0.0996†	0.0552†	-7.6608*	0.09845†
Other O	0.0510	0.1656†	0.06938†	0.00794†	0.02419†	0.16843†	0.0961†	0.04863	0.0886†	-7.8047*

Notes: *Denotes own-price elasticity of product type j (j = 2, 3, 4, 5, 6 ,7 ,8 ,9 ,10) is different from own-price elasticity of product type 1 at 95% significance level.

†Denotes cross-price elasticity of product type pair (i, j) [$i \neq j, (i, j) \neq (2,1)$] is different from cross-price elasticity of product type pair (2, 1) at 95% significance level.

3.7. CONCLUSION

The organic food market has experienced tremendous growth. Along with the rapid growth of organic products, new product features have also emerged and prospered. Although how organic assortment, price, and promotions drive retailer performance has been studied in previous works (Ngobo, 2011; Bezawada & Pauwels, 2013), the extant literature does not, however, provide a clear understanding of how other product-related (style, brand, nutrition, etc.) and seller-related factors influence consumers' preferences when choosing between organic products and conventional product. In response, we study how consumers make complex purchase decisions involving organic products among numerous other non-organic related attributes. By doing so, we also seek to find the best assortment mix for retailers that carry both organic products and conventional products.

Our main findings suggest that organic condition, product style, and seller attributes are all highly influential in shaping consumers' purchasing decisions. Further, the relationship between organic and conventional products is much more nuanced and context-specific than previously shown. We find organic products always have a higher own-price elasticity than conventional products. Our results suggest that even organic consumers are willing to pay a higher price, they are also sensitive to organic prices. This phenomenon holds true even for the most health-conscious consumers----the Organic Greek yogurt consumers. In fact, Organic Greek yogurt yields the highest own-price elasticity, suggesting even the core organic consumers are price sensitive. Therefore, retailers should carefully price their organic products, so that consumers would not be driven away from the high organic pricing.

From cross-price elasticity perspective, the asymmetry between organic products and conventional products suggests that price change in conventional products has less effect on organic products than vice-versa, consistent with the asymmetric price competition literature (Sethuraman & Srinivasan, 2002). However, this effect is also content-specific. Where in some product categories such as All-Natural yogurt and Creamy yogurt, price change in conventional products has a greater effect on organic products. This finding suggests that consumers have different preferences for different product specifications. Manufacturers and retailers should carefully study consumers' preferences in order to set the optimal price for their products.

In addition, we find that a low price strategy does not work well for organic products either. As we could see from the example of Organic All-Natural yogurt, the low unit price for this product category does not result in low own-price elasticity. Neither does the low unit price increase more market share when other product categories increase price.

Finally, we find that Conventional Creamy yogurt and All-Natural yogurt are close substitutes for Organic Greek yogurt. Therefore, we find evidence that there is a group of "health-conscious" consumers as well as a group of consumers that focuses on the taste and texture of food. Retailers could utilize such information and optimize their assortment mix to attract and retain their customers.

The following limitations from our study provide promising trajectories for further analyses. First, our study involved only one product (yogurt) and product type (diary). Future research may consider replicating our analysis across other product categories. Second, due to the data limitation, we do not have accurate store locations, therefore we could not form the accurate choice set a consumer face when purchasing a product. Future research may consider using more accurate geographic information to form a more accurate choice set for consumers. Finally, we utilized data from the year 2008 to 2011, where recent development in organic markets may have further changed consumers' attitudes and habits towards buying organic products. Future research could utilize more recent data to replicate our analysis.

CHAPTER 4

CONCLUSION

In this dissertation, we investigate the impact of organic products on conventional products and on retailer assortment planning. Specifically, we seek to answer the following research questions.

- Does conventional product variety increase or decrease when organic product is introduced (or its variety increases) at the store level?
- Does the control of assortment decisions in the supply chain affect assortments between organic and conventional products?
- How consumers evaluate organic products when there are multiple features and attributes of the organic product, and directly evaluate the cannibalization effect of conventional products on organic products.

Results from our study show that introducing organic products will result in an increase in conventional product variety. This positive relationship between organic product introduction and conventional product variety also holds when stores increase their organic product offerings. We also find that when manufacturers are more concentrated, and therefore more powerful in the supply chain and have control over product assortment decisions, stores tend to have a less positive relationship between organic product and conventional product variety. Similarly, when retailers are more powerful with a strong private label presence, they tend to reduce branded conventional products and increase private-label conventional products when introducing organic products. In addition, we find organic products always have a higher own-price elasticity than conventional products, suggesting that even organic consumers are willing to pay a higher price, they are also sensitive to organic prices. We also find that the cross-price elasticities between organic products and conventional products are asymmetry. This asymmetry cross-price elasticity suggests that price change in conventional products has less effect on organic products than vice-versa.

Our studies make several theoretical contributions to research streams in assortment planning and supply chain management. First, we show that introducing and increasing organic product variety has a greater market expansion effect than its cost effect associated with increasing product variety. That is, organic products, thanks to their specialized group of customers, stimulate the demand for a variety of conventional products within the same category. Therefore, instead of switching out the existing conventional products with new organic products, retailers are better off further increase the conventional product variety in the same product category. On the other hand, we also confirm that the cost effect is significant when retailers face strict shelf space constraints. Second, we show that the relationship between organic and conventional product assortments are subject to the supply chain power and governance between the retailers and manufacturers. In particular, we consider that supply chain power resides with a concentrated group of manufacturers or retailers with strong private label presence. We show that these two mechanisms lead to different results for conventional product variety. With a smaller, concentrated manufacturer group, the retailer has less power and control over product assortment decisions. And in this case, we show that a manufacturer’s concerns of cost efficiency associated with organic products have a stronger effect on retailer assortment decisions, thereby mitigating the market expansion effect for manufacturer brands. Moreover, we show that retailers with a strong private label presence may leverage the pattern of expansion of organic product variety as an opportunity to increase their private label conventional products and reduce their reliance on national brand conventional product variety. Third, we find organic products always have a higher own-price elasticity than conventional products. Our findings suggest that even though organic consumers are willing to pay a higher price, they are also sensitive to organic prices. Fourth, we find that the cross-price elasticity is asymmetry between organic products and conventional products. However, this effect is also content-specific. In some product categories such as All-Natural yogurt and Creamy yogurt, price change in conventional products has a greater effect on organic products. This finding suggests that consumers have different preferences for different product specifications. Manufacturers and retailers should carefully study consumers' preferences in order to set the optimal price for their products.

Practitioners could also benefit from our findings of this study in a number of ways. For retailers that have not yet launched organic products on their shelves, this study points to the benefit of overall store sales from the introduction of organic products. Retailers could use organic products to attract new variety-seeking consumers, who could also buy conventional products as well. This way stores are also encouraged to add variety for conventional products also. Increasing both organic product variety and conventional variety will result in higher category level sales. Our study also suggests retailers to carefully study their customers' specific preferences on both organic and conventional products. Further, they could leverage such information and select the best assortment mix within a product category to achieve better performance. From a manufacturer's perspective, by facing the growing pressure of supplying organic products and meeting retailers' demand for more variety in conventional products, manufacturers should invest in clear product differentiation of their national brands (for organic and conventional products) so that customers can be wooed away from the retail stores' organic or private label brands. In addition, since producing both conventional products and organic products may be costly, manufacturers could consider mergers and acquisitions with small organic product producers, thereby increasing their overall product portfolios.

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