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Essays on Greek Yogurt in the US Market

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ABSTRACT

Essays on Greek Yogurt in the US Market

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The US yogurt market has been volatile in the last decade, marked by striking sales increases and dramatic market structure changes. According to an industry report,[1] dollar sales of yogurt in 2017 reached $8.8 billion—a more than 80% increase from 2007. Such remarkable sales growth can be attributed to the rapid rise of Greek yogurt, which has been established as a subcategory accounting for more than half of the category sales. Chobani, a new entrant, has played an important role in this development, as it elevated Greek yogurt from niche to a mass-market trending product. With the increasing popularity of Greek yogurt, Chobani has grown to be one of the largest brands in the highly competitive yogurt category. The two large category incumbents, Dannon and Yoplait, launched Greek yogurt two years later than Chobani. Dannon was able to grow quickly through subsequent introduction of successful new products, whereas Yoplait experienced a significant sales decline and has lost its number-one leading position. As a result, the market structure has changed radically from a duopoly to a three-firm oligopoly. This dissertation studies those dynamic changes in the yogurt category caused by the development of Greek yogurt and the entry of Chobani.

[1] "The Yogurt Market and Yogurt Innovation, 3rd Edition" by the market report firm Packaged Facts.

The first chapter introduces the dynamic changes in the US yogurt category from 2006 to 2015. I first show empirical evidences on the rapid sales growth and the dramatic changes in brand market share. Then, I describe how those changes occurred by documenting the entry and market expansion of Chobani, the competitive response from Dannon and Yoplait, as well as the changes in consumer purchases. This chapter comprehensively describes the development of Greek yogurt in the US market and the consequent category evolution. It delineates the transition process from regular to Greek yogurt.

After introducing the dynamic changes in the category, I conduct two empirical investigations. First, in chapter 2, I examine the effect of learning on consumer purchase of Greek yogurt. Because Greek yogurt is relatively new in the US market, consumers may be uncertain about their preference and have to learn how much they like Greek yogurt from consumption. To study the role of uncertainty in Greek yogurt purchase, I construct a demand model of consumer learning and apply it to individual level purchase data. Using the estimated parameters from the demand model, I then predict brand shares when uncertainty on Greek yogurt is removed. The results show that Greek yogurt brands can gain much larger market shares if consumers had full information about their preference. This simple simulation experiment suggests that learning plays an important role in consumer purchase of Greek yogurt.

The third chapter studies the entry effect of Dannon and Yoplait on Chobani's store sales. In 2010, Dannon and Yoplait launched Greek yogurt. In many stores the two brands entered, Chobani had been on shelves for a long time. The store sales of Chobani in those stores could decrease due to the increased competition from Dannon and Yoplait. On the other hand, Greek yogurt was a developing subcategory with very few brand offerings, the introduction of new varieties from the two big brands can expand the subcategory that might benefit

Chobani. Thus, the impact of the two incumbents' subcategory entry on Chobani's sales is ambiguous. Chapter 3 investigates this empirical ambiguity using a differences-in-differences framework. With proper control for store sales growth trends, I find that Chobani's sales decreased in stores that Dannon entered, whereas sales in stores that Yoplait entered had an increasing trend a few weeks following Yoplait's entry. The asymmetric entry impact can be caused by the product and price differences of the two category incumbents.

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CHAPTER 1

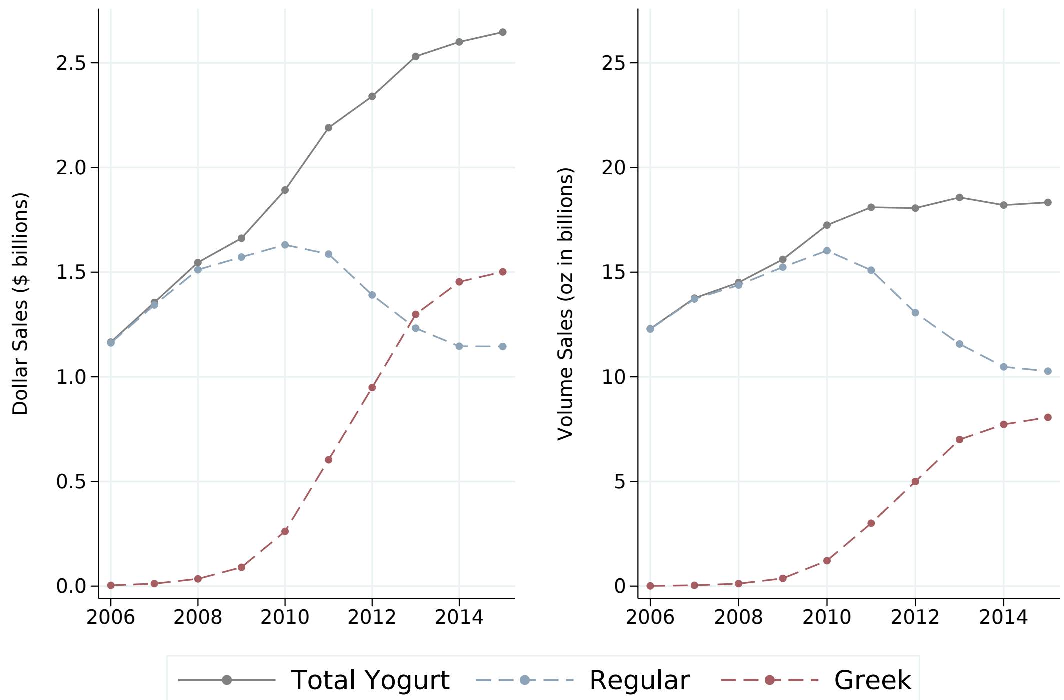
The Development of Greek Yogurt in the US Market

Yogurt has been one of the fastest-growing food categories in the US market. Figure 1.1 shows the dollar and volume sales of yogurt from the Kilts Nielsen Retail Scanner Data. We see a year-on-year increase in sales from 2006 to 2015, especially the dollar sales, which were doubled during this time period. The increase in dollar sales was first driven by regular yogurt which grew at a steady rate before 2009. Greek yogurt was initially a market niche with negligible shares. It began to rise in 2008 and soon started growing rapidly, becoming the primary driver of category growth. The compounded annual growth rate of Greek yogurt for the five-year period from 2010 to 2015 was over 42%. In 2015, Greek yogurt sales soared to $1.5 billion, contributing to more than half of total yogurt sales. The striking growth of Greek yogurt came at the cost of regular yogurt sales, which started to decline sharply in 2011 and eventually decreased to a smaller size than the 2006 level.

Compared to the large and continuous growth in dollar sales, the volume of yogurt sold increased at a slower rate. In fact, after the initial increase before 2011, volume sales of yogurt stayed relatively flat, even during the fast-growing period of dollar sales. The contrast in the growth rates between dollar and volume sales suggests the category expansion is attributed more to the high prices for Greek yogurt than to a large increase in consumption.

Figure 1.1 also shows, although Greek yogurt exceeds regular yogurt in dollar sales, more than half of the consumption is still from regular yogurt. The evolution of yogurt sales

Figure 1.1. Yogurt Sales in Nielsen Retail Stores from 2006 to 2015

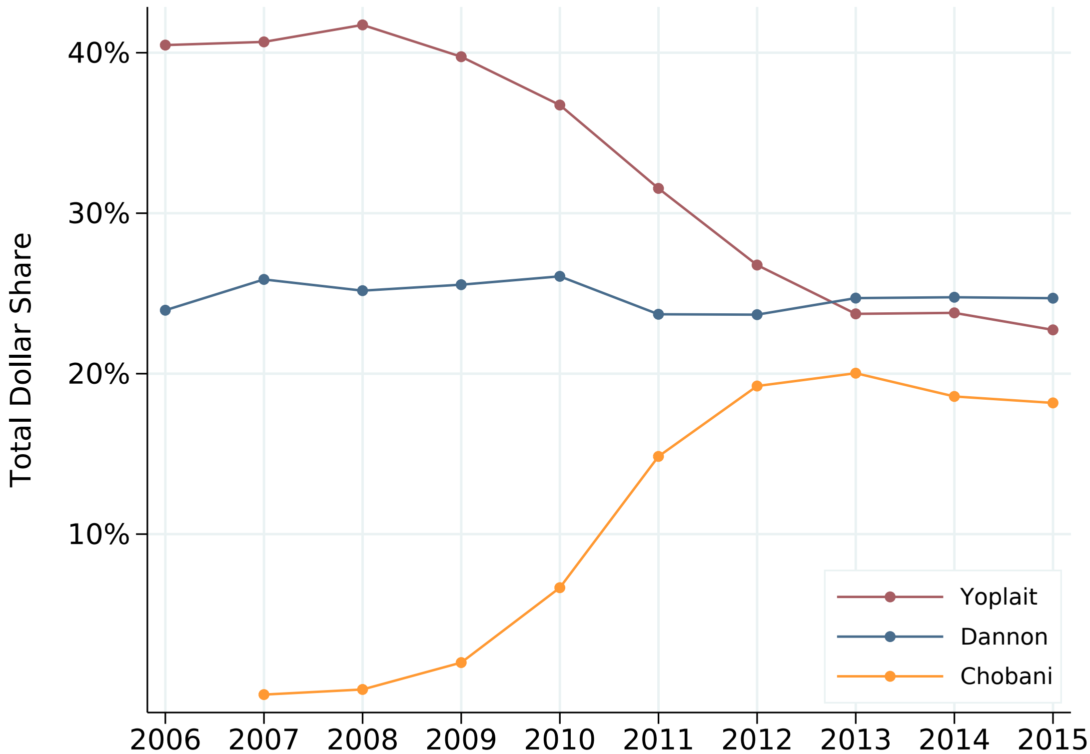


This figure plots the yogurt dollar and volume sales in the years 2006-2015. The data is from stores tracked by the Kilts Nielsen Center every year in this time period.

suggests the category has split into two subsegments, with Greek yogurt accounting for more dollar sales and regular yogurt accounting for more consumption.

The transition from regular to Greek yogurt is first led by Chobani, a new entrant that has grown to be one of the largest national yogurt brands. Figure 1.2 shows the market share of the three major yogurt brands from 2006 to 2015. Before the entry of Chobani, two large national brands, Dannon and Yoplait, had controlled the yogurt category for decades with a combined share of over 70%. Yoplait was the leading brand with more than 40% of market share, followed by Dannon holding a share of about 25%. Both brands were available in national markets with a large portfolio of regular yogurt, but no Greek yogurt.

Figure 1.2. Market Share of Major Brands



The figure shows the dollar share of yogurt for Chobani, Dannon, and Yoplait in stores that reported to the Kilts Nielsen Center every year from 2006 to 2015.

In November 2007, Chobani entered with Greek yogurt only. It was first available in a few stores in the New York market, and then gradually introduced Greek yogurt to more stores and markets. With the expanding distribution, Chobani gained market shares quickly, especially in the period from 2009 to 2012 when its share grew at a double-digit rate. In 2013, Chobani reached about 20% of category sales and became the third largest yogurt brand in the US market. Meanwhile, Yoplait experienced a dramatic share decline and lost almost half of its share in 2006. Dannon, however, maintained a relatively stable share, with only a moderate decrease around 2011. Figure 1.2 shows Dannon finally surpassed Yoplait in 2013 and became the largest yogurt brand.

The differences in share changes between the two large incumbents stem from the marketing strategies they adopted for Greek yogurt. Both of them entered the Greek segment two years later than Chobani. Dannon shifted its focus to Greek yogurt earlier and subsequently launched new products that gained instant market success. Yoplait's sales decline is due to its reliance on regular yogurt and the lack of successful Greek yogurt products. The rest of this chapter proceeds with documenting those dynamic changes in detail by describing Chobani's entry and store expansion, the competitive reaction from Dannon and Yoplait, and the competition in the Greek yogurt segment after entry. In the final part, I also show the changes in consumer yogurt purchase during the category transition.

1.1. Chobani's Entry and Store Expansion

The yogurt category in the US market is well-differentiated with various brand-flavor-variety combinations. Innovation is constant and frequent new product introduction has been the primary driver of the category growth. Before the surge of Greek yogurt, most new products of regular yogurt, also called conventional American-style yogurt or traditional yogurt, were featured in introducing new flavors, reducing calories, or targeting specific consumer needs by adding fibers, probiotics (e.g., Dannon Activia). Greek yogurt, also called Greek-style yogurt or strained yogurt,[1] differs from regular yogurt with its thicker consistency and higher protein content, which result from straining liquid whey out of the raw milk, thereby eliminating much of the water. The straining process preserves a higher

[1]Greek yogurt is not a uniquely defined product with a federal standard of identity. Any company that claims its product to be Greek yogurt must conform to the federal standard for yogurt, but the claim of being Greek is a connotation, not a well-defined designation. Some yogurt marketed as Greek yogurt uses dairy protein concentrates instead of the straining process to achieve a higher protein content. The two most commonly cited consumer characteristics to identify Greek yogurt are a higher protein content and thicker consistency—not the manufacturing process employed or ingredients used. In this dissertation, I use the term "Greek Yogurt" to include any products marketed as Greek yogurt without regard to the production process or ingredients used.

percentage of protein, with a typical 6-ounce serving of Greek yogurt containing 15-20 grams of protein, compared with 9 grams in regular yogurt. Since a significant portion of lactose, sodium, and carbohydrates contained in the liquid whey is also removed, Greek yogurt is lower in those nutrients than regular yogurt and is often considered healthier than regular yogurt.

Producing Greek yogurt from the straining process involves a much higher cost because it uses three times more milk than the amount used when producing the same amount of regular yogurt. In addition, the mass production of Greek yogurt from the straining process requires a special type of machinery that is not needed for making regular yogurt. Thus, given the novel product features as well as the distinct manufacturing process, Greek yogurt is considered to be a more disruptive innovation compared with the new regular products previously introduced in the category.

Greek yogurt has been in the US market since the 1990s. The first brand to introduce America to Greek yogurt was Fage.[2] However, for years Fage remained as a niche product only available in specialty stores. In 2007, Fage was sold mostly in high-end chains such as Whole Foods and Trader Joe's. Table 1.1 shows the prices, market share, and distribution of main yogurt brands in 2006 and 2007 in Nielsen retailer stores. Fage was the largest Greek yogurt brand, with very limited distribution and prices almost three times as expensive as regular varieties. The total market share of Greek yogurt was less than 1%. The rest of the market was dominated by regular yogurt, among which Dannon and Yoplait were the two largest national brands that contributed nearly 70% of dollar sales.

[2]Fage initially imported Greek yogurt from Greece. It began to produce Greek yogurt in 2008 when its plant opened in Johnstown, NY.

Table 1.1. Yogurt Market Summary Statistics in 2006-2007

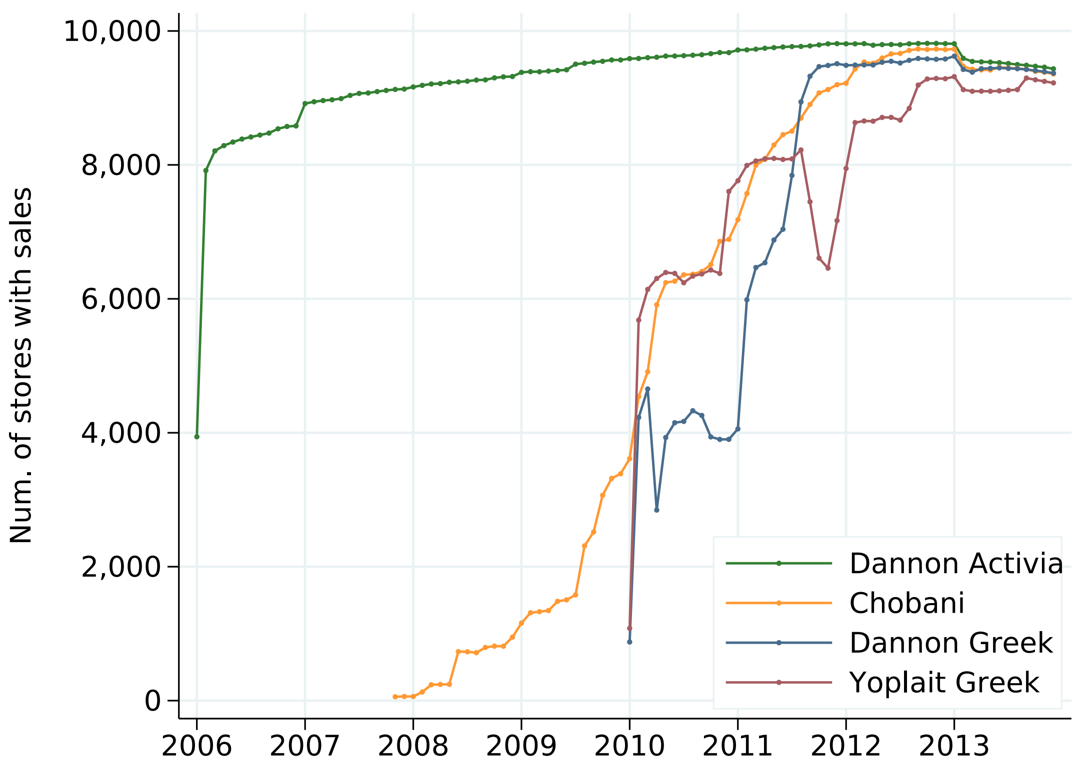
Brand	2006				2007			
	Price (6oz)	Dollar share	Volume share	% ACV	Price (6oz)	Dollar share	Volume share	% ACV
Yoplait	0.69 (0.18)	40.57%	36.95%	99.87%	0.69 (0.18)	41.37%	39.33%	99.88%
Dannon	0.76 (0.19)	24.21%	19.69%	99.61%	0.78 (0.20)	26.28%	21.60%	99.94%
Other regular	0.57 (0.27)	34.88%	43.26%	99.48%	0.60 (0.28)	31.50%	38.80%	99.83%
Fage	2.01 (0.38)	0.29%	0.09%	17.91%	2.01 (0.36)	0.75%	0.23%	28.15%
Chobani	-	-	-	-	1.55 (0.16)	0.00%	0.00%	0.69%
Other Greek	1.30 (0.23)	0.05%	0.02%	6.67%	1.62 (0.54)	0.09%	0.04%	30.36%

This table shows the summary statistics for yogurt with unit size 4 to 8 ounces and a package size no larger than 4-pack. Other Greek yogurt in the table includes Voskos from Sun Valley dairy in California, The Greek God, and Stonyfield. The measure of distribution, % ACV, is calculated as the annual dollar sales of yogurt in stores where a brand had sales divided by the yogurt sales from all the stores in the sample. Each column reports the mean from stores that reported to the Kilts Nielsen Center every year from 2006 to 2015. Standard deviations of prices are given in parentheses.

In Novermber 2007, Chobani entered a grocery chain in Long Island, New York. Its product, called Chobani Greek yogurt, was available in five flavors in a single-serving size of 5.3 ounces, and one flavor in 16 ounces. Table 1.1 shows that prices for Chobani Greek yogurt were set to be lower than Fage, but still twice as expensive as regular yogurt. Contrary to the previous Greek yogurt brands that were only sold in specialty stores or gourmet food sections, when first launched in that grocery chain, Chobani insisted its products be placed on the yogurt shelves alongside popular regular yogurt brands. Chobani aimed to reach the mainstream market through mass-distribution channels of grocery store chains.

Store expansion of Chobani started with that grocery chain and initially spread across stores in the Northeast. As a new entrant with novel product features and with no distribution network, Chobani entered retailer stores at a very slow pace compared to new products from large brands in the category. Figure 1.3 illustrates the store diffusion of new yogurt products including Dannon Activia, Chobani, and Greek yogurt launched later by Dannon and Yoplait. Activia was a new product developed by Dannon featuring the benefits of probiotics and it was first launched in 2006. As shown in Figure 1.3, Dannon Activia was sold in almost all stores immediately after its introduction. The initial store entry of Chobani, on other hand, was more gradual with a linear evolving pattern over time. Chobani made its products available in a small number of stores in the first year of its entry. The store-by-store success of Chobani continued until the third quarter of 2009, when the entry speed accelerated. Even with a faster store entry rate, Chobani did not appear in many stores until 2012. The store roll-outs of Chobani span across more than four years.

Figure 1.3. Store Availability of New Yogurt Products



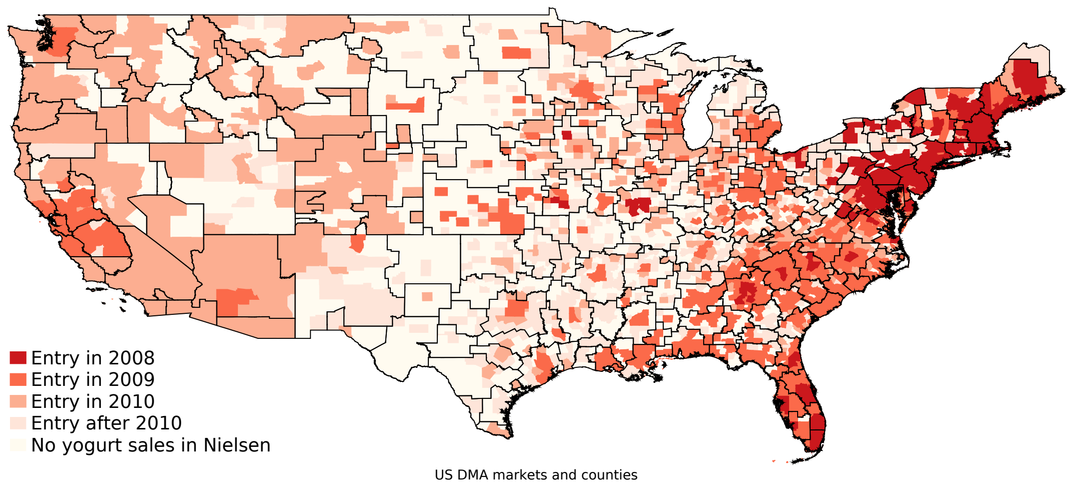
The figure plots the number of stores selling each yogurt brand at the monthly level. The sample includes stores that reported yogurt sales to the Kilts Nielsen Center every year from 2006 to 2015. As long as brand sales are observed in a store at any week in a given month, the store will be counted as an available store for the brand.

Such a store entry pattern is unique for an entirely new entrant like Chobani or for products with novel features, whereas leading brands such as Dannon and Yoplait tend to launch new products on a large scale. The Greek yogurt introduction from Dannon and Yoplait differs from Chobani with a stepwise pattern. Both firms launched new products in a large number of stores concurrently, especially Yoplait, which made its Greek yogurt available in more stores immediately after entry than Chobani did in more than two years. Although Dannon Greek was available in fewer stores in 2010, it later entered the rest of the stores at a faster speed than Chobani.

Another interesting observation is the comparison between Dannon Activia and Dannon Greek. Although both new products were launched by the same firm, Dannon Activia appeared in most stores immediately after being launched, whereas the store expansion of Dannon Greek was phased over two years. The possible explanation is that Dannon Greek is a more radical innovation than Dannon Activia in the sense that it not only has a different texture and nutritional content, but also is made from an entirely different procedure using special machinery. The store entry of Dannon Greek thus faced more uncertainty in demand and was constrained by supply side as well, two difficulties Chobani also faced.

In addition to the continuous linear store entry pattern, Chobani entered different geographic markets sequentially, another contrast with the national launch observed for other new yogurt products. As a manufacturer located in Upstate New York, Chobani started its regional entry from the markets close to its plant. Figure 1.4 shows the entry time of Chobani at the county level on a US DMA map. Almost all of the entered markets of Chobani in 2008 are in the Northeast. While the contagion continued spreading along the east coast, Chobani did not extend to the connected markets in the west. Instead, it appeared into some stores on the west coast in 2009, and shipped yogurt all the way from the New York factory.[3]

Figure 1.4. Chobani's Entry Map



The figure plots the observed earliest entry time of Chobani at the county level on a US DMA map. The earliest entry time is defined as the first year in which Chobani sales are observed in at least one store in the county.

The subsequent store entry of Chobani in 2010 was mostly in distant markets on the west coast. Chobani did not reach the rest of the US until much later. This observed spatial roll-out pattern differs from a contagion process that would otherwise spread to markets in the middle before jumping to the west. Considering that the distribution of yogurt is direct store delivery, long distance shipping from the east to the west coast is more costly than serving the markets in the middle first. Therefore, the observed roll-outs strategy was driven by factors such as Greek yogurt demand or entry barriers rather than distribution efficiency.

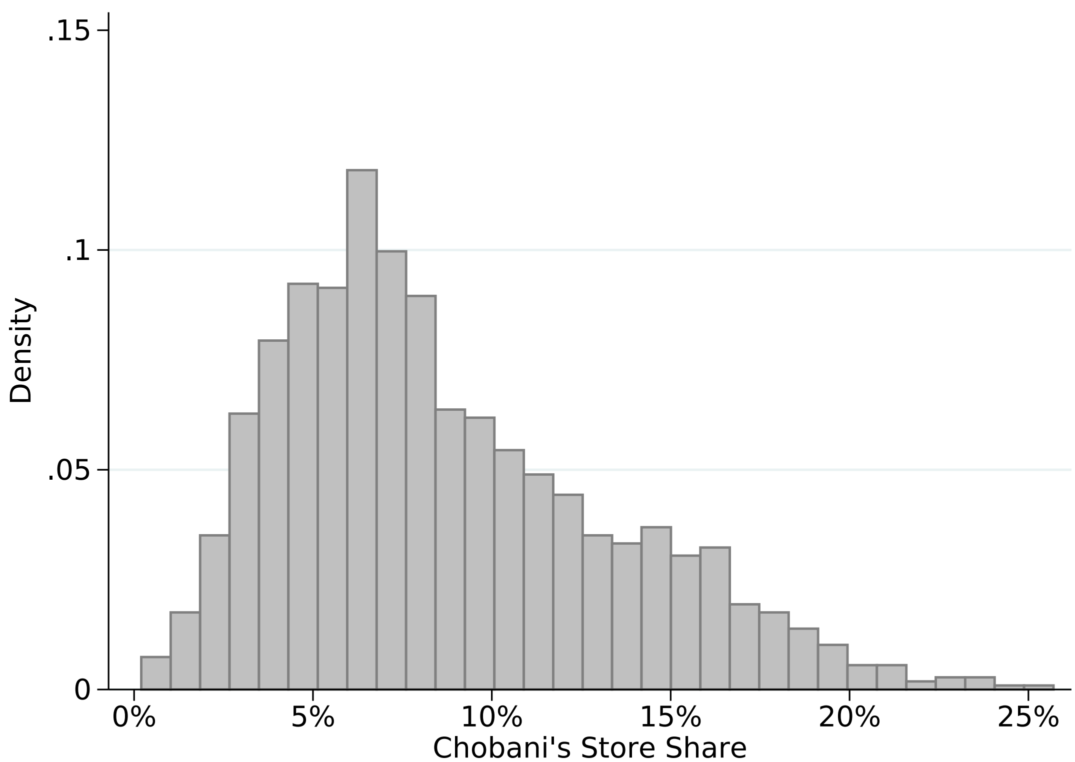
After two years of store roll-outs, Chobani reached a distribution of 38% in $\%ACV$ in Nielsen retailer stores. It gained a larger share than Fage, becoming the leading Greek yogurt brand. In 2009, Chobani's market share reached 2% of total yogurt dollar sales, with

[3]Chobani opened the second factory later in Twin Falls, Idaho. The new plant was put into production in 2013. Before that all its yogurt products were shipped from the New York factory.

a considerable variation across different geographic markets. In Northeast markets, where it entered first, Chobani had the highest store coverage and captured 8.8% of dollar shares. In markets on the west coast, Chobani was not available until late 2009. With very limited store availability, Chobani accounted for less than 0.1% of all yogurt sales in those late markets.

In addition to the variation across markets, Chobani's share also differed across stores it entered. The across store variation is illustrated in Figure 1.5, which shows Chobani's shares in the last two quarters in 2009 from stores it had previously entered. On average, Chobani captured 8.7% of store shares, ranging from less than 1% to over 25%. It accounted for more than 15% of yogurt sales in some stores and less than 5% in many other stores.

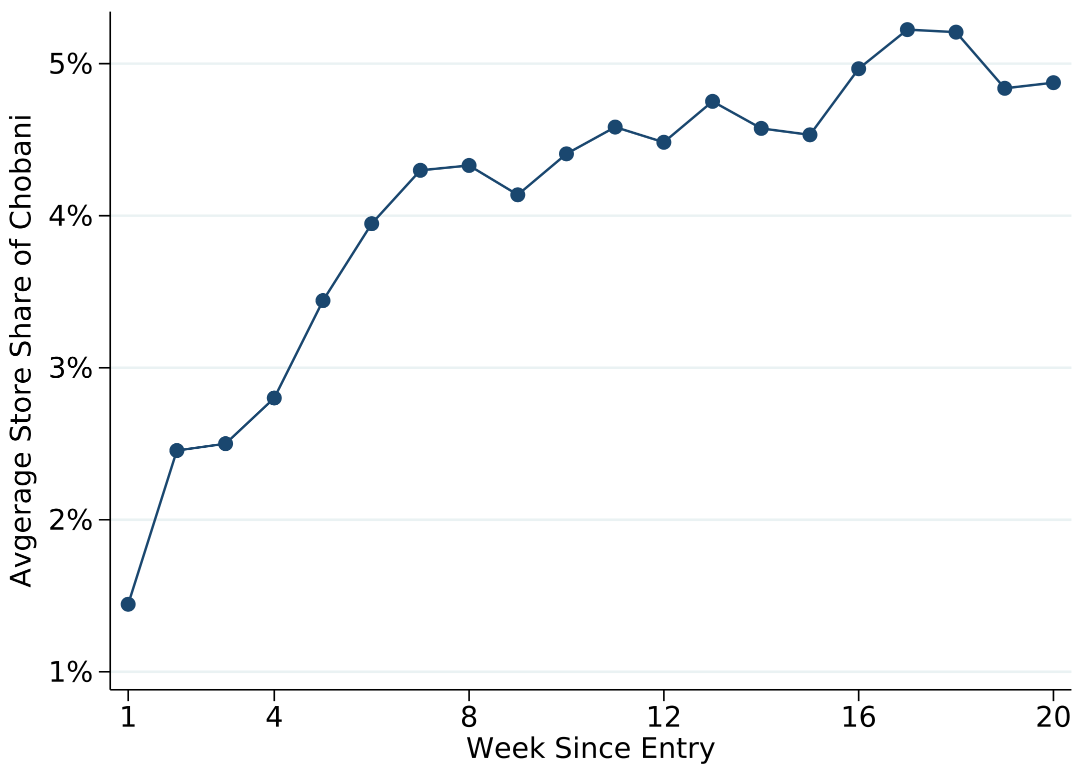
Figure 1.5. Chobani's Store Share in Q3-Q4 in 2009



This figure plots the histogram of Chobani's store shares in the last two quarters in 2009. The data is from 1,317 stores Chobani entered before the 3^{rd} quarter of 2009.

The store share of Chobani depends largely on how long it had been on store shelves as sales need time to take off after the new product launch. Figure 1.6 illustrates how Chobani gained shares over time in the entered stores. Immediately after entry, Chobani began to take shares quickly, especially in the first few weeks. The share growth slowed down after about 8 weeks, but kept showing an upward trend. Chobani achieved such store success even without promotions and investment in traditional media advertising campaign.[4]

Figure 1.6. Store Share Growth of Chobani



The figure plots Chobani's store shares in the first 20 weeks after entry. The data is from stores Chobani entered before the 3^{rd} quarter in 2009. The entry timing of Chobani varies across stores. Each observation shows the average share Chobani obtained in the n^{th} week after Chobani's entry.

[4]Chobani launched its first major traditional media advertising campaign in February 2011, according to a New York Time report, see https://www.nytimes.com/2011/02/17/business/media/17adco.html.

In 2009, the Greek segment accounted for 5.6% of all yogurt dollar sales. Chobani was the largest brand with about half of the segment sales, followed by Fage and Stonyfield.[5] The two brands charged higher prices for their Greek yogurt than Chobani. All the three Greek yogurt brands were expanding store distribution and Chobani was the one that grew fastest.

1.2. Dannon and Yoplait's Launch of Greek Yogurt

As the new entrant was surging into popularity with Greek yogurt in more and more markets, Dannon and Yoplait focused on developing regular yogurt. They both launched new products that gained great market success in the period from 2006 to 2009. In fact, some of their new regular yogurt products made the top 10 on Symphony IRI New Product Pacesetters,[6] including Dannon Activia in 2006, Danon DonActivia yogurt drinks in 2007, and Yoplait Fiber One in 2009. Even though their sales did not grow as fast as the Chobani sales, both firms saw a positive increase in revenue as the yogurt category was growing.

The quick development of Greek yogurt and Chobani finally caught the attention of Dannon and Yoplait. The two category incumbents launched their versions of Greek yogurt at the same time in January 2010. They both simply added "Greek" after the brand name to distinguish the new products from their regular yogurt. Table 1.2 shows the prices, market share and store distribution of major yogurt brands in 2010 and 2011. Yoplait Greek was released with five different flavors and a price about 15% less than Chobani. Dannon, however, set a slightly higher price for Dannon Greek which was available in four different

[5] Stonyfield is a yogurt brand controlled by Groupe Danone, the parent company of Dannon. Its Greek yogurt, called Stonyfield Organic Oikos Greek yogurt, was first produced by Agro-Farma, the parent company of Chobani, and then by another dairy manufacturer when its relationship with Agro-Farma fell apart in 2008, according to a lawsuit, see https://casetext.com/case/stonyfield-farm-inc-v-agro-farma-3.

[6] IRI(Information Resources, Inc.) publishes an annual report on New Product Pacesetters that ranks the top products in their first full year of sales.

flavors. Although the lower prices for Yoplait Greek might be purely a competition strategy, Yoplait Greek may nevertheless have a lower production cost because it was produced using milk protein concentrate instead of from the straining process, a standard procedure used by Chobani, Dannon and other Greek yogurt brands.[7]

Table 1.2. Yogurt Market Summary Statistics in 2010-2011

Brand	2010				2011			
	Price (6oz)	Dollar share	Volume share	% ACV	Price (6oz)	Dollar share	Volume share	% ACV
Yoplait	0.69 (0.19)	38.51%	40.97%	99.96%	0.71 (0.18)	30.09%	34.53%	99.94%
Dannon	0.72 (0.21)	24.03%	23.67%	99.93%	0.79 (0.24)	21.05%	22.45%	99.93%
Other regular	0.64 (0.29)	22.33%	28.01%	99.33%	0.66 (0.31)	18.53%	25.18%	99.82%
Chobani	1.34 (0.21)	7.40%	4.06%	79.55%	1.33 (0.21)	16.68%	10.26%	98.32%
Fage	1.89 (0.38)	3.45%	1.25%	87.18%	1.74 (0.39)	4.51%	2.05%	90.33%
Yoplait Greek	1.13 (0.14)	1.11%	0.67%	80.69%	1.11 (0.15)	1.79%	1.25%	86.40%
Dannon Greek	1.42 (0.16)	0.65%	0.31%	54.42%	1.34 (0.20)	2.92%	1.71%	94.79%
Other Greek	1.72 (0.50)	2.53%	1.07%	89.38%	1.50 (0.53)	4.42%	2.59%	97.76%

This table shows the summary statistics for yogurt with unit size between 4 to 8 ounces and a package size no larger than 4-pack. The measure of distribution, % ACV, is calculated as the annual dollar sales of yogurt in stores where a brand had sales divided by the yogurt sales from all the stores in the sample. Each column reports the mean from stores that reported to the Kilts Nielsen Center every year from 2006 to 2015. Standard deviations of prices are shown in parentheses.

In addition to the differences in price and product, the entry of Yoplait and Dannon also differs in the number of stores and markets entered. Figure 1.3 shows Dannon Greek and Yoplait Greek were launched simultaneously in many stores. The large entry scale can be attributed to the established distribution network and market power the two large incumbents accumulated over the years. Yoplait entered many more stores than Dannon. This can be seen from both Figure 1.3 and Table 1.2. In the first year of entry, Yoplait

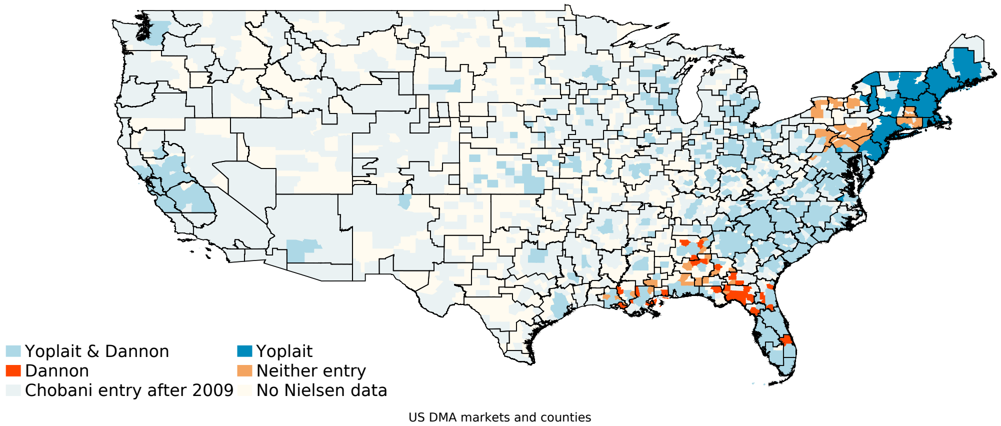
[7]General Mills' Greek yogurt is "not yogurt at all", lawsuit claims, see https://www.foodnavigator-usa.com/Article/2012/06/12/Yoplait-Greek-yogurt-lawsuit.

reached a distribution of 80.69% in $\%ACV$ in Nielsen stores. Dannon's distribution, on the other hand, covered only 54.42% in 2010. Dannon's smaller entry scale was due to the limited production capacity it initially had, as revealed by an interview with industrial experts. Since Dannon produced Greek yogurt using a straining process, it required investment in a type of special machinery that was not widely available in the market in 2010. Yoplait did not face such constraints in manufacturing facilities because it made Greek yogurt by adding milk concentrate.

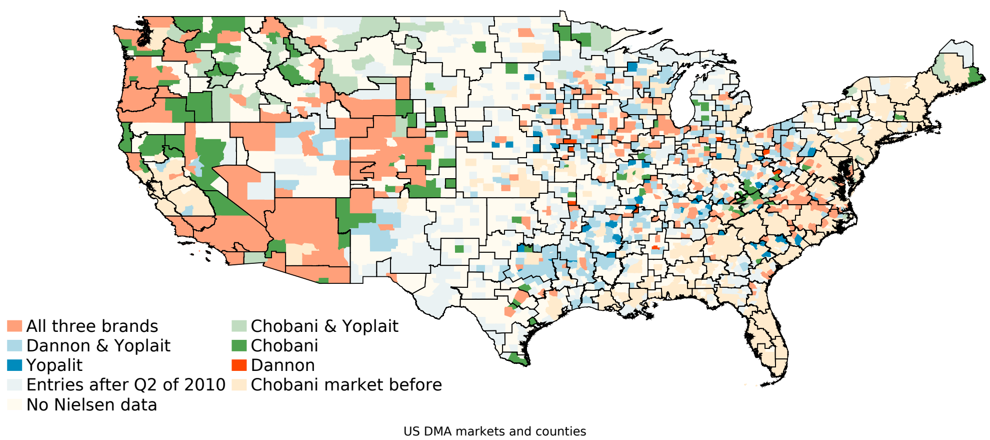
Dannon not only entered fewer stores, but was also more selective in its choice of markets to enter. Figure 1.7 describes the entry market overlap of Dannon, Yoplait, and Chobani in a DMA and county map. Plot (a) at the top panel shows that Dannon and Yoplait entered most of the markets that Chobani entered before 2010, especially Yoplait, which entered almost everywhere Chobani entered previously. Dannon, however, did not enter any stores in the Northeast markets, where Chobani originated and had the largest market shares by the time of the two incumbents' entry. New entries by the three brands in the first two quarters of 2010 are depicted in plot (b) of Figure 1.7. It shows that the three brands jointly entered many markets in the west. Chobani seems to focus on conquering the markets in the west, where it had little presence before 2010, whereas Dannon and Yoplait entered some markets that Chobani did not enter in the southern and central regions. Among the three brands, Dannon had the least market coverage.

Despite the advantage in distribution network and larger advertising budgets, Dannon and Yoplait gained very little success in Greek yogurt after the subcategory entry. Table 1.2 shows Greek yogurt accounted for over 15% of all yogurt sales in 2010. Chobani's share reached to 7.4%, half of the segment sales, while Yoplait Greek and Dannon Greek together captured less than 2% shares. Yoplait Greek initially had a larger share than Dannon Greek

Figure 1.7. Entry Map of Greek Yogurt in Q1 & Q2 of 2010



(a) Entry of Dannon & Yopplait in Previous Chobani Markets



(b) New Entries in Markets Chobani Did not Enter before 2010

The figure plots the market entry of the three major brands in the first two quarters in 2010. The top panel shows the entry of Dannon and Yoplait in markets Chobani entered before 2010, while the bottom one shows the new entries of all three brands in 2010. A market is considered to be entered by a brand if sales of the brand are observed in at least one store in the market.

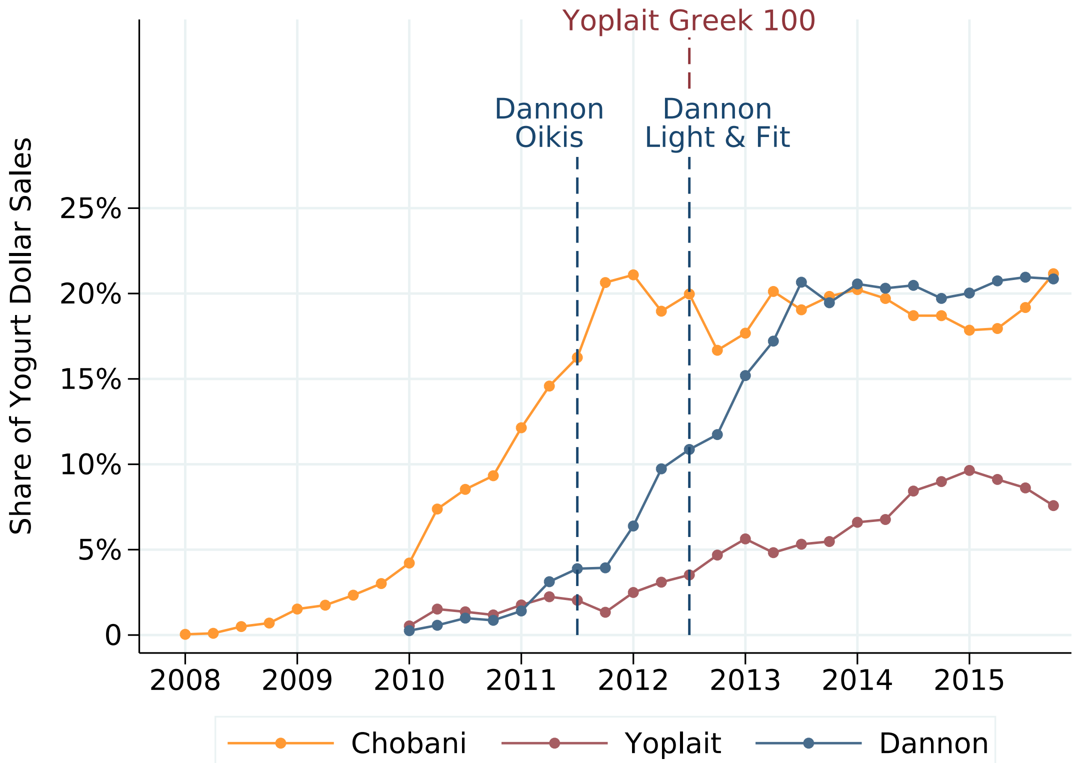
in 2010, possible due to the higher distribution coverage. However, in the second year of entry, Dannon Greek grew much faster and surpassed Yoplait Greek in both dollar and volume shares, with a reduced price and a much broader distribution.

1.3. Competition after Entry

The subcategory entry of two big incumbents did not prevent Chobani from growing fast. In fact, Chobani experienced triple-digit growth in market shares in both 2010 and 2011. Figure 1.9 presents the share of Greek yogurt for the three brands, along with the time of some critical new product launches. It shows that Chobani captured more than 20% of all yogurt dollar sales in the last quarter of 2011. However, the rapid growth in Chobani shares slowed down in 2012 when Dannon began to rise in the subcategory.

The quick catch-up of Dannon started from one important marketing strategy implemented in August 2011, which was to rebrand Dannon Greek as Dannon Oikos Greek. The rebranding did not involve changes in product formula, but rather new packaging and new marketing. The word "Oikos" is taken from Stonyfield Oikos Organic Greek yogurt, one of the earliest Greek yogurt products that had been in market since 2007. And Stonyfield is a brand from the same parent company as Dannon, Groupe Danone. The rebranding strategy led to the takeoff of Dannon's sales in the subcategory. As Figure 1.9 shows, after the rebranding, the share of Dannon increased at a much higher rate than other brands, and its growth was further fueled by the introduction of Dannon Light & Fit Greek yogurt, a vertical integration of Greek yogurt with its largest regular product line, Light & Fit. Dannon Light & Fit Greek yogurt gained great market success and was ranked the number one top selling new yogurt products 2011. With those two successful new product launches, Dannon was able to keep increasing its share rapidly, and it became the leader of Greek

Figure 1.9. Share of Major Greek Yogurt Brands



This figure plots the quarterly shares of Greek yogurt for the three major brands from 2008 to 2015. The dashed lines mark the time of some important new product launches. The data is from stores that reported to the Kilts Nielsen Center every year in the plotted time period.

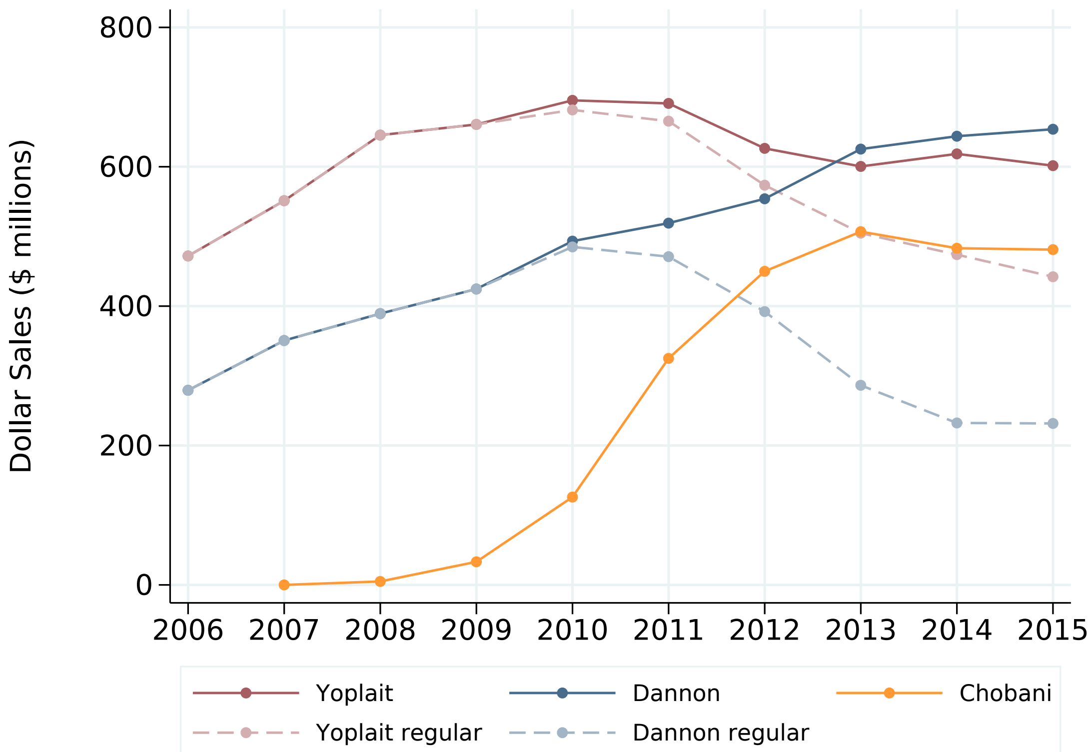
segment expansion as Chobani's share growth became flat or even negative after 2011. Dannon's fast growth continued until the end of 2013 when its Greek yogurt and Chobani each controlled about 20% of yogurt sales. Although Dannon entered much later in the segment, it eventually captured slightly more shares than Chobani.

Figure 1.9 shows Yoplait never grew its Greek yogurt share as fast as Dannon and Chobani. Initially, Yoplait Greek gained more shares than Dannon Greek, with a broader distribution in the first year of entry, but soon fell behind Dannon's fast growth. To catch up with its competitors, Yoplait reformulated its Greek yogurt twice before 2012, each with thicker-texture, new flavors, and brighter-colored packing. New UPCs were constantly being added in Nielsen retailer stores, and none of them was observed to lead to remarkable changes in shares. The most successful Greek yogurt from the brand is Yoplait Greek 100, a product with 100 calories that was released in August 2012, the same time as the introduction of Dannon Light & Fit Greek yogurt. The two new products were both developed to target the calorie cautious consumer segment. Yoplait Greek 100 was ranked as the second best selling new yogurt product in its first year on shelves, following Dannon Light & Fit Greek yogurt.[8] Figure 1.9 shows the share growth of Yoplait was flat relative to Dannonn and Chobani. The lack of more successful Greek yogurt products had put Yoplait in a poor position to compete.

Regular yogurt sales of Dannon and Yoplait have shrunk since 2011. Figure 1.10 depicts the changes in dollar sales over years for Dannon, Yoplait, and Chobani from 2006 to 2015. Both Dannon and Yoplait grew their sales year by year before 2010. After entering into the Greek segment, the total dollar sales of Dannon continued to increase, driven by the quick growth of its Greek yogurt, whereas Yoplait began to lose sales since 2011. As the category transitioned to Greek yogurt from regular yogurt, Yoplait failed to capture shares in the developing segment and it was surpassed by Dannon in 2013. Within the regular yogurt segment, Yoplait stabilized its leading position with a sales level less than a decade ago and less than the sales the new entrant Chobani captured in the Greek segment. Dannon's regular yogurt sales dropped even more, accounting for about one-third of its total yogurt sales in 2015.

[8] Yogurt Greek 100 was the largest new product launch of Yoplait in more than 20 years, with over $150 million sales in the first year, see http://fortune.com/2017/05/22/general-mills-yoplait-greek-yogurt/?iid=sr-link2.

Figure 1.10. Dollar Sales of Major Brands

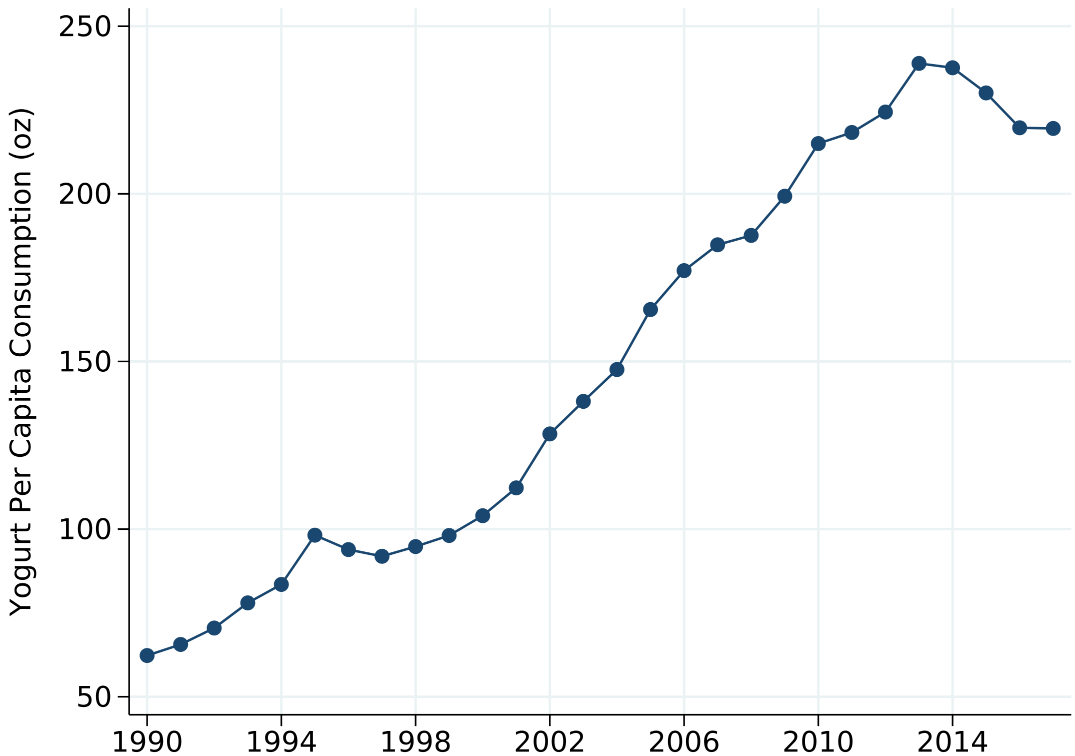


The figure shows the dollar sales of the three major brands in Nielsen retail stores. The data sample only includes stores which reported to the Kilts Nielsen Center every year from 2006 to 2015. For Dannon and Yoplait, the solid line plots the total yogurt sales and the dashed line plots the sales of regular yogurt.

1.4. Changes in Consumer Yogurt Purchases

Yogurt is a developing category in the US market. The per-capita consumption is much lower than in European countries. Figure 1.11 shows a year-by-year increase of yogurt consumption since 1990. Especially after the year 2000, per-capita consumption of yogurt grew continuously at a very high rate. The quick development of Greek yogurt did not lead to a faster increase in total yogurt consumption. On the contrary, Figure 1.11 shows the yogurt consumption grew slowly after 2010. The long lasting growth finally stopped and the per-capita consumption began to decrease in 2014. This is possibly caused by the high prices of Greek yogurt or the development of other healthy food.

Figure 1.11. Yogurt Per-capita Consumption in US



The data source of this plot is from USDA. The Economic Research Service of USDA provides annual per-capita consumption estimates for major dairy products including yogurt. The per-capita consumption is calculated by dividing domestic disappearance by the U.S. resident population plus armed forces overseas. The plotted time period is from 1990 to 2017.

Table 1.3 presents the purchase summary of households in the Nielsen panel. It shows an increasing trend in yogurt penetration during the time period from 2006 to 2015. More and more consumers are purchasing from the category. About 82% of households in the panel purchased yogurt at least once in 2015, a large increase from 75% a decade previously. The total dollar spending on yogurt increased monotonically from year to year, driven first by the increasing spending on regular yogurt and then by the growth of Greek yogurt from 2010. The amount spent on regular yogurt decreased until it accounted for half of the category spending.

Table 1.3. Yogurt Purchase from Nielsen Household Panel in 2006-2015

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Panel size	37,786	63,350	61,440	60,506	60,658	62,092	60,538	61,097	61,557	61,380
Yogurt penetration	75.4%	76.6%	77.9%	79.3%	81.1%	81.9%	81.1%	81.5%	82.1%	82.3%
Yogurt spending ($)	34.1	36.3	39.9	41.7	44.2	49.3	52.4	55.4	57.1	57.6
Regular yogurt spending ($)	34.0	36.1	39.3	40.2	39.5	38.8	34.6	29.7	28.8	28.7
Consumption (in oz)	404	411	423	444	458	477	466	465	456	450
Regular yogurt consumption	404	410	421	438	436	419	366	313	291	283
Average price paid (per 6oz)	0.53	0.56	0.59	0.60	0.64	0.67	0.73	0.77	0.80	0.82
Num.of UPC each trip	1.8	1.8	1.8	1.8	1.8	1.8	1.7	1.7	1.7	1.8
Num.of brand each trip	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
Regular segment	99.1%	98.5%	95.7%	90.4%	71.2%	51.9%	41.4%	29.9%	27.4%	27.6%
Greek segment	0.0%	0.0%	0.1%	0.3%	1.1%	2.9%	6.1%	9.4%	9.4%	10.2%
Regular and Greek segment	0.9%	1.4%	4.2%	9.3%	27.7%	45.2%	52.6%	60.7%	63.2%	62.2%

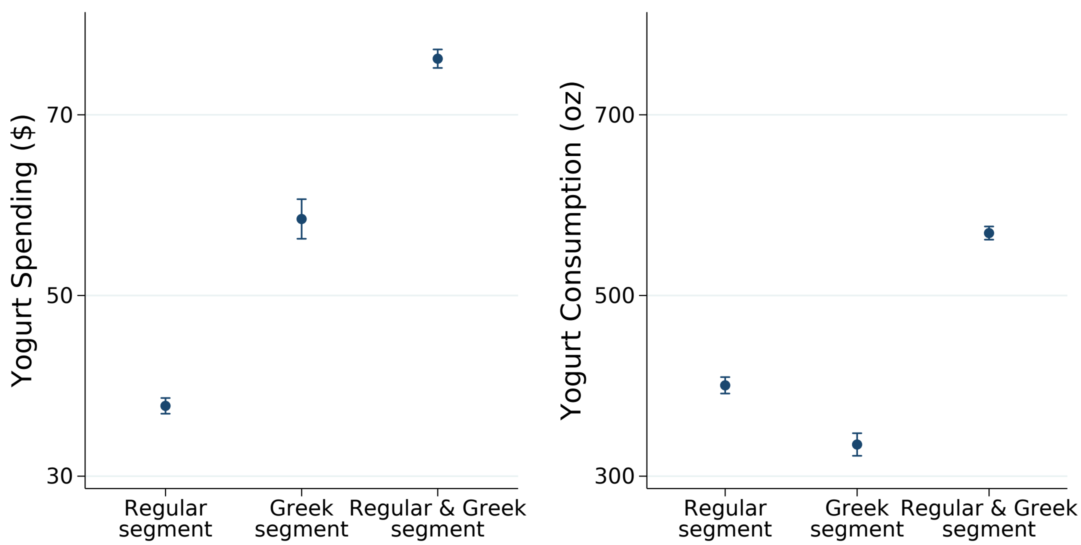
The table reports the purchase summary of yogurt from the Nielsen household panel. The panel size shows the total number of households who recorded their purchases to Nielsen. And the yogurt penetration is calculated by dividing the number of households who ever bought yogurt for at least once by the panel size. All other variables including yogurt spending, consumption, and price paid are calculated only for households who bought yogurt in that year. The last three columns report the fraction of yogurt buyers who bought only regular yogurt, Greek yogurt, or both regular and Greek yogurt.

Consistent with Figure 1.11, the total yogurt consumption began to drop in 2012 after six years' continuous growth. The decrease in regular yogurt consumption occurred earlier in 2010, and in total we see a reduction of 30% in 2015 compared to that in 2007. Greek yogurt consumption was lower than regular yogurt even though the spending on Greek yogurt was slightly higher. Households did pay higher prices on average for yogurt because Greek yogurt is more expensive. In spite of shelves exploding with various new products, the number of UPCs and brands purchased on each yogurt trip did not increase as households, on average, bought about two flavors and one brand.

The last three columns of Table 1.3 list the fraction of households that purchased only regular or Greek yogurt, and those who purchased both regular and Greek yogurt. Over 90%

of yogurt buyers never purchased Greek yogurt before 2010, the year in which the number of Greek yogurt buyers began to increase quickly. From 2010, more and more consumers purchased both regular and Greek yogurt. However, by 2015, over one-quarter of consumers had not bought Greek yogurt yet. The Greek segment, including consumers only purchasing Greek yogurt, was the smallest, only about 10% of the total yogurt buyers. As shown in Figure 1.12, households that purchased both Greek and regular yogurt spent and consumed more yogurt than the other two segments. The average percentage consumption of Greek yogurt among those who purchased both Greek and regular yogurt in 2015 was 43.1% with a standard deviation of 30.2%, suggesting considerable heterogeneity in Greek yogurt purchase across consumers.

Figure 1.12. Yogurt Spending and Consumption by Segments in 2015



The figure shows the mean and 95% standard errors in yogurt spending and consumption for each consumer segment. The data is from Nielsen household panel purchases in 2015.

1.5. Conclusion

This chapter empirically documents the development of Greek yogurt in the US market. Greek yogurt was a market niche with less than 1% of market share a decade ago. It has now grown to be a subcategory accounting for more than half of the category sales. The rapid growth of Greek yogurt was first led by Chobani, a new entrant of yogurt manufacturer that has become one of largest national brands in the highly competitive category. In this chapter, I first describe the entry and unique store expansion pattern of Chobani, and how it led to the initial popularity of Greek yogurt in the US market.

Dannon and Yoplait were the two big incumbents that controlled the yogurt category for decades. The two brands both entered the Greek yogurt subcategory two years later than Chobani. Their Greek yogurt initially gained very little share compared with Chobani. However, Dannon shifted marketing strategies to Greek yogurt earlier than Yoplait. It launched new products that became the strongest competitors of Chobani. Meanwhile, Yoplait remained its focus on regular yogurt. Its reformulation of Greek yogurt came too late to capture the growing potential in the new subcategory. As the Greek segment grew quickly at the cost of regular yogurt sales, Yoplait eventually lost its number one leading position to Dannon. Although the sales growth of Chobani slowed down in the competition with Dannon, it captured 20% market share of all yogurt sales, becoming the third largest brand in the US market.

In the category's transition from regular to Greek yogurt, households increased dollar spending, but decreased total yogurt consumption. Because Greek yogurt is more expensive, the average price paid for yogurt was about 30% higher in 2015 than the price paid in 2010. Most of the households bought both regular and Greek yogurt, especially households with high spending and consumption, and yet more than one-quarter of households in Nielsen panel did not buy Greek yogurt in 2015.

This dissertation proceeds in chapter 2 with a yogurt demand estimation to evaluate the effect of consumer learning on Greek yogurt brand shares. Chapter 3 studies the impact of incumbents' entry on Chobani's store sales using a differences-in-differences method.

CHAPTER 2

Consumer Learning and Greek Yogurt Brand Shares

When Dannon and Yoplait launched Greek yogurt in 2010, Chobani had already obtained considerable store shares in some markets. Although the two large brands had established strong positions in the yogurt category for years, their Greek yogurt sales did not grow as fast as Chobani. In fact, combined the Greek yogurt from the two brands captured a total share that was less than one-third of the share Chobani gained in 2010. The poor performance of Dannon and Yoplait in the Greek subcategory can be attributed to many factors. For instance, Yoplait's product is considered "fake" Greek yogurt because it was made by adding milk protein concentrate instead of from a straining process, and Dannon Greek yogurt was priced slightly higher than Chobani. Among all possible explanations, learning and inertia in consumer choices, if they exist, can play an important role. This possibility is more likely to be true given that Dannon and Yoplait entered the subcategory two years later than Chobani. And uncertainty for Chobani may have already resolved for some households by the time of the two incumbents' entry. To investigate this issue, I estimate a yogurt demand that allows for both learning and inertia in consumer behavior, using which I can predict brand market shares in the absence of uncertainty.

Learning is important for experience goods like yogurt. Consumers do not know whether or how much they actually like the product until they gain consumption experience. Due to a lack of previous purchases, a newly launched product is associated with uncertainty in consumer preference. Risk averse consumers are thus more reluctant to buy the new product than they would be if they had more information. Hence, a product launched later will be more disadvantaged than an existing product that has been available in the market for a while and whose uncertainty has therefore been resolved.

Moreover, if consumers exhibit inertia in that they are more likely to buy products that they purchased in the past, the chance of choosing a new product will be even smaller because it does not have the sales record that an existing product might have. Considering that Dannon and Yoplait entered the Greek subcategory two years later than Chobani, some consumers had already purchased and discovered their preference for Chobani. Switching to Dannon or Yoplait Greek would occur with a smaller likelihood if those consumers had already developed inertia to Chobani. For consumers who had not previously bought Chobani, we would not expect such an effect.

In this chapter, I investigate the role of learning and choice inertia in yogurt purchases and how they affect the market share of Greek yogurt brands. The following section first summarizes previous literature, followed by an introduction of the demand model and the data used for this study. After showing model estimation results, I run a simple counterfactual simulation to explore the changes in market share of Greek yogurt brands in the absence of preference uncertainty. I then conclude my results in the last section.

2.1. Literature Review

In the marketing literature, an extensive body of studies investigates how learning and choice inertia affect consumer purchase patterns and brand market share. In this section, I only survey previous works that are most relevant to this study. For a detailed and complete review of learning models, see Ching et al. (2013).

Erdem and Keane (1996) develop a Bayesian learning model and apply it on household purchases of laundry detergent. It is the pioneer paper using learning models in estimation of structural models of consumer choices. Different from the simple learning models that appeared earlier in marketing literatures, their model can handle forward-looking consumers who learn from multiple information sources and is feasible to estimate. In their paper, households have uncertainty in one unobserved product attribute, namely the cleaning power of each detergent brand, which can be learned both by purchasing and by exposure to advertisements. All households are assumed to hold the same initial belief on the unobserved product quality. Each purchase then conveys a signal that can be used to update the belief on households' intrinsic preference for the purchased item. In addition, households can also receive exogenous signals from TV advertising. Erdem and Keane (1996) find the learning model they develop describes the observed purchase pattern substantially better than a flexible model without learning. They also find that sustained advertising has a positive long-run effect when consumer learning is considered.

Ackerberg (2003) estimates a learning model on purchase of a newly introduced yogurt product by Yoplait. Similar to Erdem and Keane (1996), he also considers learning from both consumption and advertising. Moreover, the paper focuses on distinguishing two different learning effects from advertising: informative versus prestige effects. Ackerberg (2003)'s model is richer than the one used in Erdem and Keane (1996) in the sense that it allows for individual-level heterogeneity both in prior beliefs and the true intrinsic match value.

Osborne (2011) extends the literature by allowing for switching cost as another source of state-dependence in addition to learning. He applies a forward-looking learning model to individual level panel data on purchase of liquid laundry detergent. The paper finds evidence for both learning and switching cost in consumer choices. It is worth mentioning that both

Ackerberg (2003) and Osborn (2011) allow for a continuous distribution of consumer type and assume a one-shot learning process in which uncertainty will be resolved after one purchase occasion.

Another related work also in the yogurt category is Zou (2014), who adopts a consumer choice model with learning and inertia to study the pricing of a new product, specifically Chobani. To link learning and inertia to price, he also assumes a simple supply side model. The counterfactuals reveal that low prices at the product launch can incentivize consumer loyalty when learning exists. The current study differs from Zou (2014) in many ways. For example, a major difference is that I consider learning for multiple brands, whereas Zou (2014) focuses on the period when Chobani was the only Greek yogurt brand that consumers need to learn about.

2.2. Data and Yogurt Demand Model

The data used in this chapter are from the A.C. Nielsen Homescan Consumer Panel (hereafter, HMS) and Retailer Scanner Panel (hereafter, RMS). The HMS data are a panel of household purchases. They track all the shopping trips made by each participating household with detailed information on the shopping date, characteristics of the visited store (e.g., retailer identity, channel type, and Zip-3 location of the store), UPC code, prices, and quantities for each purchased item. The RMS data contain store scanner data over a subset of US retailers. The sales data are at the weekly level and include store characteristics, prices, and quantities sold for all UPCs sold in stores owned by each participating retailer.

For both HMS and RMS datasets, I select the time period from 2008 through 2011 because the store entry and household adoption of all major Greek yogurt brands in my study can be observed in this period. Data after 2011 are available, but I do not use them for this study, because firms changed marketing strategies that are irrelevant to uncertainty and consumer learning.[1] And the purpose of this study is to investigate whether the initial launch of Dannon and Yoplait Greek yogurt would have been more successful in the absence of preference uncertainty and consumer learning.

I use the HMS data to construct a time series of yogurt purchases for each household. The HMS panel consists of about 60,000 households each year from 2008 through 2011. I only consider households who reported to Nielsen every year, who made trips to grocery and discount stores, and who stayed in the same Zip-3 area. I therefore end up with a sample size of 31,371 households. For this set of households, I further drop 8.9% of them because they did not purchase yogurt at all in the sample period. Hence, only yogurt buyers are considered in this study.

Next, I select households based on their purchase of single-serving yogurt, which I define as yogurt with a serving size between 4 to 8 ounces per container. This selection rule excludes yogurt for kids, because most kid-sized yogurt has less than 4 ounces per container. Greek yogurt for kids came much later and is thus not considered in the selected time period. Purchases of large-size yogurt are also removed because households usually have different reasons for buying large-size versus single-serving yogurt. In addition, I also exclude UPCs with a package size larger than four containers. After applying this selection rule, I only remove less than 6% of all yogurt trips from the sample.

I then exclude households with relatively few or infrequent yogurt purchases. In this step, households who purchased yogurt less than five times in a year are removed from the sample. The major concern about including infrequent yogurt buyers is the identification

[1]For example, Dannon reformulated Dannon Greek into Dannon Oikos Greek and launched big marketing campaigns. Dannon's sales were observed to increase rapidly after the rebranding in Chapter 1. Unfortunately, the campaign data cannot be observed in the Nielsen data.

challenge when very few purchases are observed. Additionally, those households may have a very large value for outside options that are not considered in my model. This step excludes a large number of households, resulting in a sample size of 9,344 households.

In the next step, I further remove households who purchased multiple brands in a single shopping trip for more than 5% of total yogurt trips. The model I adopt is a discrete choice model in which only one brand is purchased in a shopping occasion. Households who tend to buy multiple brands violate the single unit purchase assumption, and their behavior should be described in other models, such as the multiple discreteness model (see Dubé, 2004). A total of 4,884 households survive this selection rule.

A final and critical selection criterion I apply is whether a household mostly purchased yogurt from RMS stores where I can observe weekly product sales and prices. This selection condition is necessary because I need to know the set of products available in a shopping trip and their prices for the model estimation. Unfortunately, such information cannot be observed in the HMS data because households only record characteristics of the purchased product. The purchase data contain no information on other alternative items in the shopping store.

Product availability is an important issue for this study because the entry time of most Greek yogurt brands varies across markets and stores, a contrast from the simultaneous store entry of previous new regular yogurt introduced by large brands. Ignoring product availability can produce biased estimation for household preference. Consider, for example, a scenario in which Dannon Greek yogurt is not available in a particular shopping trip and thus cannot be purchased. If I do not know this fact and put Dannon Greek in the choice set of that shopping trip, the model will underestimate the preference for Dannon Greek, based on the observed low purchase probability that in fact is due to unavailability of the product. If a household shopping trip can be matched to an RMS store, then I can infer from the sales data the set of available brands during the shopping trip.

Another reason for only choosing shopping trips made in RMS stores is to construct price series. Most regular yogurt, especially large brands such as Dannon and Yoplait, are sold in almost every store. Product availability is thus not a big concern. However, unless the household bought the product, prices cannot be observed from the HMS data. To solve this problem, I impute prices from the RMS data. In particular, I first match a household shopping trip to an RMS store based on store or retailer identity and purchase date. Then I can use the store weekly prices to fill in the unobserved prices for items that were not purchased.[2] For a much more detail description of how I construct price series from RMS stores, see Appendix A.

The final sample I use in this study consists of 706 households whose yogurt trips were made in RMS stores for at least 95% of their total yogurt trips. In total, I observe 50,265 yogurt trips. Table 2.1 shows the yogurt purchase summary for households in the sample. The number of Greek yogurt trips increased year by year. The average prices paid for Greek yogurt decreased over time, but were still much higher than the prices for regular yogurt.

I assume households are choosing between seven yogurt brands: three regular brands including Dannon, Yoplait, and store brand, and four Greek yogurt brands including Chobani, Fage, Dannon Greek, and Yoplait Greek. All other yogurt products are aggregated together as "Others". Combined the choice share of other brands only account for less than 8% in the data.

[2]Note that the RMS data only contain information for UPCs with sales in the week. In other words, if a UPC has zero sales on shelves in the week, it will not appear in the data. Thus, this simple match may introduce some bias. Because I group UPCs into brands and focus on large brands, I expect the bias, if any, will not significantly affect the results.

Table 2.1. Household Purchase Summary

Year	Num. of yogurt trips		Prices (cents per 6 oz)	
	Regular	Greek	Regular	Greek
2008	12,490	47	10.18 (2.70)	25.85 (8.48)
2009	12,983	55	9.94 (2.47)	24.62 (9.80)
2010	12,557	353	9.89 (2.32)	20.16 (5.12)
2011	10,877	903	10.11 (2.27)	21.22 (4.69)

The sample used is the entire sample of purchase events, which contains 50,265 observations and 706 households. The prices are imputed from RMS sales data. For a detail description of the price construction, see Appendix A.

Table 2.2 reports the choice share and price for the four Greek yogurt brands. Before 2010, Chobani and Fage had negligible shares due to the limited store distribution. Dannon Greek captured a larger share than Yoplait Greek in 2010 although it fell behind at first. The combined share of Dannon and Yoplait was smaller than the share of Chobani. 258 households purchased Greek yogurt in the sample. Most of them purchased Chobani or Yopalit Greek as their first Greek yogurt brand. Although Fage was in the market earlier than other brands, its price was much higher and only about 12% of Greek yogurt buyers chose it as the first Greek yogurt to buy.

In the model, I assume household i has a true match value (also called intrinsic preference) for the yogurt brand j, denoted by δ_{ij}. If j is a regular yogurt brand, δ_{ij} is known to the household as regular yogurt has been available in the market for decades and the sample only includes frequent yogurt buyers. Thus no associated uncertainty is present in regular yogurt preference. Greek yogurt, on the other hand, is newly introduced with novel product attributes. The household does not have full information and is learning about δ_{ij} for all Greek yogurt. Before the first purchase of a Greek product j, household i holds a prior belief

Table 2.2. Greek Yogurt Choice Shares and Prices

		Chobani	Fage	Dannon Greek	Yoplait Greek
Fraction of households who purchased the brand as the first Greek yogurt brand		34.5%	12.02%	20.93%	32.56%
2008	Choice share	0.19%	0.18%		
	Price	18.08 (1.32)	33.96 (3.75)		
2009	Choice share	0.30%	0.12%		
	Price	18.74 (3.02)	38.94 (3.75)		
2010	Choice share	1.56%	0.25%	0.15%	0.77%
	Price	18.72 (3.05)	32.47 (5.22)	23.65 (2.80)	18.40 (2.35)
2011	Choice share	4.10%	0.97%	1.52%	1.08%
	Price	20.22 (3.38)	27.85 (6.80)	22.04 (2.96)	17.93 (2.02)

The first row reports the fraction of households who purchased the brand as her first Greek yogurt brand. The sample only includes 258 households who ever purchased Greek yogurt. The data used for choice share and price is the entire sample of purchase events, which contains 50,265 trips and 706 households. Standard deviations of prices are given in parentheses.

on δ_{ij}, and

$$\delta_{ij} \sim N(\delta_{ij0}, \sigma_{ij}^2)\,, \tag{2.1}$$

where δ_{ij0} is the household's expected intrinsic preference when she has never purchased Greek yogurt j, and σ_{ij}^2 accounts for the degree of uncertainty.

If product j is purchased at time t, the household will experience utility δ_{ijt}^E. In the case of one-shot learning that assumes the household can resolve the uncertainty of Greek yogurt preference immediately after the first purchase, $\delta_{ijt}^E = \delta_{ij}$, the true match value of j. For all t after the first purchase trip of j, the true value of δ_{ij} is known and thus no further learning occurs. Since yogurt is an experience good with product attributes that are relatively easy to learn, one-shot learning is a reasonable assumption.

An alternative assumption is that each consumption experience can only provide noisy signals on the true match value. With the remaining uncertainty, learning continues in all subsequent shopping trips. In this case, I follow the specification in most learning literature and assume the experience utility is a linear combination of the true match value and a noise term ν_{ijt},

$$\delta^E_{ijt} = \delta_{ij} + \nu_{ijt} \, , \tag{2.2}$$

where, $\nu_{ijt} \sim N(0, \sigma^2_\nu)$ captures random shocks (e.g., inherent product variability, variation in perception, etc).

I assume the household is a Bayesian learner who updates her belief after observing each consumption signal. Consider, for example, that household purchases j at time 1 and observes δ^E_{ij1}. In the next shopping trip, her belief on the true match value of j becomes $\delta_{ij} \sim N(\delta_{ij1}, \sigma^2_{ij1})$, and

$$\delta_{ij1} = \frac{\sigma^2_{ij0}}{\sigma^2_{ij0} + \sigma^2_\nu}\delta^E_{ij1} + \frac{\sigma^2_\nu}{\sigma^2_{ij0} + \sigma^2_\nu}\delta_{ij0} \, , \tag{2.3a}$$

$$\sigma^2_{ij1} = \frac{1}{(1/\sigma^2_{ij0}) + (1/\sigma^2_\nu)} \, . \tag{2.3b}$$

Let $N_{ij}(t)$ denote the total number of consumption experiences household i has with brand j up to period t. Then, at time t, the posterior distribution of the intrinsic preference is $\delta_{ij} \sim N(\delta_{ijt}, \sigma^2_{ijt})$, and

$$\delta_{ijt} = \frac{\sigma^2_{ij0}}{N_{ij}(t)\sigma^2_{ij0} + \sigma^2_\nu}\sum_{\tau=1}^{t}\delta^E_{ij\tau}d_{ij\tau} + \frac{\sigma^2_\nu}{N_{ij}(t)\sigma^2_{ij0} + \sigma^2_\nu}\delta_{ij0} \, , \tag{2.4a}$$

$$\sigma^2_{ijt} = \frac{1}{(1/\sigma^2_{ij0}) + N_{ij}(t)(1/\sigma^2_\nu)} \, , \tag{2.4b}$$

where $d_{ij\tau} = 1$ if consumer i purchases product j at time τ.

Note that the posterior variance σ^2_{ijt} is a deterministic function of preference parameters and thus can be observable to the household. The posterior mean δ_{ijt}, however, contains random elements $\{\delta^E_{ij\tau}\}^t_{\tau=1}$, and can be re-written as

$$
\begin{aligned}
\delta_{ijt} &= \frac{\sigma^2_{ij0}}{N_{ij}(t)\sigma^2_{ij0}+\sigma^2_\nu}\sum_{\tau=1}^{t}\delta^E_{ij\tau}d_{ij\tau} + \frac{\sigma^2_\nu}{N_{ij}(t)\sigma^2_{ij0}+\sigma^2_\nu}\delta_{ij0} \\
&= \delta_{ij} + \frac{\sigma^2_{ij0}}{N_{ij}(t)\sigma^2_{ij0}+\sigma^2_\nu}\sum_{\tau=1}^{t}\nu_{ij\tau}d_{ij\tau} + \frac{\sigma^2_\nu}{N_{ij}(t)\sigma^2_{ij0}+\sigma^2_\nu}\xi_{ij0}\,,
\end{aligned}
\tag{2.5}
$$

where $\xi_{ij0} = \delta_{ij0} - \delta_{ij}$ is the initial perceptual bias and $\nu_{ij\tau}$ is the random noise term in the experienced utility. Equation 2.5 shows, as consumption experience accumulates, δ_{ijt} will converge to δ_{ij}, the true preference.

The utility household i derives from a yogurt product j at the purchase event t is

$$
U_{ijt} = \delta_{ijt} + \beta_i P_{ijt} + \gamma_i s_{ijt} + \epsilon_{ijt}\,, \tag{2.6}
$$

where the intercept δ_{ijt} is household i's intrinsic preference for yogurt j. As discussed earlier, $\delta_{ijt} = \delta_{ij}$ is known to the household and does not vary over time when j is regular yogurt. If j is Greek yogurt and has never been bought before the purchase event t, $\delta_{ijt} = \delta_{ij0}$, the prior belief on the true match value. After the first purchase, δ_{ijt} equals the true match δ_{ij} in the one-shot learning process, and it equals the posterior mean at time t given by Equation 2.4a when learning takes multiple consumption events.

The price coefficient β_i is household i's price sensitivity and it varies by individuals. The variable s_{ijt} is a dummy variable that equals 1 if yogurt j is purchased by household i in the yogurt trip $t-1$, and 0 otherwise. So the parameter γ_i accounts for the presence of choice inertia. A positive value of γ_i indicates the household is sticky to the last purchase, and a negative value suggests evidence of variety seeking. The last term ϵ_{ijt} is the i.i.d. idiosyncratic shock that follows Type I Extreme Value distribution.

I specify a slightly different utility function for purchasing other yogurt than the seven brands,

$$U_{iot} = \delta_{io} + \beta_i P_{iot} + \gamma_i s_{iot} + \phi_i(t) + \epsilon_{iot}\,. \tag{2.7}$$

In Equation 2.7, δ_{io} is the intercept normalized to 0 for identification purposes, and P_{iot} is the weighted average prices for other brands in the store. The additional term $\phi_i(t)$ is the time trend that captures any other changes in consumer preference that are not directly modeled, such as any new product introduction, adjustments of the yogurt shelves, and so on. For simplicity I assume the time trend as a linear function of the month.

Preference heterogeneity is very important in choice models, and failure to control for individual heterogeneity may result in biased estimates of the learning process. In this study, I allow for unobserved heterogeneity for most of the individual parameters, including the true match values, coefficients of price and state-dependence. For each of these individual level parameters, I specify a normal distribution for which I estimate the mean and variance.

The set of parameters that do not vary by household include the prior means and variance for Greek yogurt brands, variance of signal noise, and the time trend for purchasing other yogurt. The homogeneity specification is for the purpose of identification. First, in the multiple consumption learning case, the prior variance σ_{ij}^2 and noise variance σ_ν^2 cannot be separately identified. Based on Equation 2.4b and Equation 2.5, only their ratio is identifiable. Therefore I set $\sigma_{ij}^2 = 1$ for all i and j. The estimate of signal variance σ_ν^2 should be interpreted relative to this normalization. Second, relying only on choice data, I cannot separately identify heterogenous prior means from the true preference δ_{ij}. For a detail identification discussion, see Shin et al. (2010). Given this limitation, I have to specify a common prior for all households, $\delta_{ij} = \delta_j$, to achieve identification.

Identification of learning and consumer inertia should also be discussed here because they are two types of state dependence nested together. In the multiple consumption learning process, I rely on the assumption that households are not learning about regular yogurt. Thus the inertia in last choice can be identified from data prior to the purchase of Greek yogurt. In the one-shot learning process, the identification can be achieved using both pre-Greek yogurt purchase and after-Greek yogurt purchase as no learning is involved after the first purchase of Greek yogurt.

One last assumption I impose about the learning process is that households are myopic and maximize per-period utility at each purchase event. To reduce computational burden, I do not model forward-looking behavior. More importantly, the main purpose of incorporating of forward looking behavior is usually to allow for experimentation, which seems less important in the yogurt purchase given its small portion of the shopping basket.

2.3. Demand Estimation Results

I estimate the demand model using the maximum likelihood method. For a household i, I first integrate the choice probability over the latent heterogenous distribution, resulting in the following likelihood function

$$\begin{aligned} \mathcal{L}_i(\theta) &= \int_{\theta_i} \mathcal{L}_i(\theta_i) df(\theta_i) \\ &= \int_{\theta_i} \prod_{t=1}^{T_i} Pr(d_{it}|\theta_i) df(\theta_i)\,, \end{aligned} \tag{2.8}$$

where T_i is the total number of yogurt trips made by household i. θ is a vector of parameters to be estimated and θ_i contains household specific parameters that can be characterized by the distribution $f(\theta_i)$. The term $Pr(d_{it}|\theta_i)$ in the second line of Equation 2.8 is the probability that the model's predicted choice equals the observed choice in period t.

In the multi-consumption learning model, the experience utility of consuming Greek yogurt contains a random noise term that cannot be distinguished from the true match value. And that signal noise is carried over to all subsequent shopping trips. Thus, compared with the mixed logit model and the one-shot learning model, we need an extra step to derive $\mathcal{L}_i(\theta_i)$, which is to integrate these persistent unobservables over the entire sequence of household i's choices

$$\begin{aligned}\mathcal{L}_i(\theta_i) &= \prod_{t=1}^{T_i} Pr(d_{it}|I_{it}, \theta_i) \\ &= \int_{\{\delta^E_{ij\tau}\}^{T_i}_{\tau=1}} \prod_{t=1}^{T_i} Pr(d_{it}|\theta_i, \{\delta^E_{ij\tau}\}^{t}_{\tau=1}) df(\{\delta^E_{ij\tau}\}^{T_i}_{\tau=1}) \,,\end{aligned} \tag{2.9}$$

where I_{it} is household i's information set by time t, and it contains all the experience utilities that are known to the household, but cannot be observed by us.

Table 2.3 presents the maximum likelihood estimates of four different models. The first two columns show estimates from a mixed logit model with choice inertia. Columns (3)-(4) contain results from a static learning model without choice inertia. Then the next specification adds choice inertia as another source of state dependence in addition to learning. The last two columns report results from a one-shot learning model when consumer inertia is also considered. In all models, I allow for individual heterogeneity for brand match values, price and choice inertia coefficients. The learning parameters and time trend for other yogurt are invariant across households.

Table 2.3. Demand Estimation Results

	Mixed logit with choice inertia		Learning without inertia		Learning with inertia		One-shot learning with inertia	
	(1) mean	(2) std.dev	(3) mean	(4) std.dev	(5) mean	(6) std.dev	(7) mean	(8) std.dev
True match value								
Dannon regular	2.078	2.160	3.174	1.871	2.676	1.745	2.589	1.753
	(0.243)	(0.166)	(0.109)	(0.036)	(0.099)	(0.041)	(0.106)	(0.047)
Yoplait regular	2.741	1.602	3.952	1.611	3.280	1.063	3.116	1.087
	(0.089)	(0.034)	(0.100)	(0.032)	(0.088)	(0.025)	(0.093)	(0.030)
Private label	1.760	1.486	1.857	2.044	2.141	2.173	1.772	1.978
	(0.084)	(0.050)	(0.079)	(0.043)	(0.078)	(0.044)	(0.081)	(0.065)
Chobani	2.730	1.150	4.850	0.429	5.391	0.131	4.470	0.032
	(0.146)	(0.048)	(0.226)	(0.070)	(0.256)	(0.080)	(0.157)	(0.083)
Fage	3.083	0.848	7.325	0.449	7.930	0.008	4.162	0.556
	(0.161)	(0.101)	(0.333)	(0.141)	(0.328)	(0.089)	(0.254)	(0.086)
Dannon Greek	2.738	1.350	5.501	0.184	5.549	0.147	4.116	0.217
	(0.098)	(0.038)	(0.315)	(0.093)	(0.384)	(0.141)	(0.198)	(0.116)
Yoplait Greek	2.277	0.717	3.787	0.615	4.049	0.759	2.902	0.684
	(0.141)	(0.137)	(0.263)	(0.157)	(0.335)	(0.145)	(0.175)	(0.150)
Initial prior mean								
Chobani			1.406		-1.297		1.982	
			(0.357)		(0.844)		(0.119)	
Fage			3.276		1.184		2.155	
			(0.489)		(1.078)		(0.170)	
Dannon Greek			-1.769		-7.213		1.313	
			(0.650)		(1.360)		(0.208)	
Yoplait Greek			1.273		-0.623		1.674	
			(0.370)		(0.872)		(0.145)	
Initial variance			0.114		0.688			
			(0.056)		(0.082)			
Other utility parameters								
Price	-0.206	0.067	-0.224	0.160	-0.211	0.121	-0.207	0.118
	(0.006)	(0.002)	(0.008)	(0.004)	(0.001)	(0.001)	(0.007)	(0.003)
Inertia	1.545	0.477			1.285	0.703	1.365	0.734
	(0.021)	(0.026)			(0.001)	(0.001)	(0.021)	(0.024)
Time trend	0.003		-0.376		-0.052		-0.080	
	(0.002)		(0.075)		(0.001)		(0.077)	
Log-likelihood	-31,642		-33,003		-30,227		-30,420	
AIC	63,322		66,050		60,502		60,886	

This table reports the estimation results from various model specifications. Standard errors are reported in parentheses.

The bottom of Table 2.3 reports the log-likelihood and AIC estimates. Of all models, multi-consumption learning with choice inertia fits the observed data best, with a slightly larger log-likelihood value than the one-shot learning model. In the multi-consumption learning model without inertia, learning for Greek yogurt is the only form of state dependence, and thus it does not account for choice inertia in regular yogurt purchases. This model has the smallest log-likelihood value. Although the mixed logit model dose not consider learning, it allows for choice inertia in all yogurt brands. The estimated log-likelihood value is larger than that from the learning model without inertia, indicating the importance of appropriately modeling state dependence.

The first seven rows are the estimated match values for the seven brands relative to other yogurt. All brands are shown to have positive match values compared to other yogurt. The estimated standard deviations for regular yogurt are larger than those for Greek yogurt, suggesting more heterogeneity is present in household tastes for regular yogurt. All learning models estimate larger match values for Greek yogurt than for regular yogurt brands.

The next four rows present the estimated parameters for the learning process. In all learning models, the estimated prior means for Greek yogurt brands are much smaller than the true match value, suggesting evidence of learning. The results from the multi-consumption learning model with inertia even show negative values for three out of the four Greek yogurt brands, indicating households had a low tendency to purchase Greek yogurt brands before consumption.

The estimates for the population mean of price coefficient are similar across all models, whereas the estimated standard deviations across households show some variation. With a higher order of state dependence, the model seems to show a greater heterogeneity in price sensitivities. In all models incorporating consumer inertia, the estimated coefficient for the lagged choice is large and positive, consistent with the inertia evidence frequently found in the yogurt category from literatures.

2.4. Impact of Learning on Greek Yogurt Market Shares

To explore the impact of preference uncertainty and consumer learning, I conduct a simple simulation experiment to compare Greek yogurt brand shares when learning exists versus when it does not. First, I simulate households' choices at each purchase event using the estimated parameters from two learning models. Based on the predicted choices, I then calculate Greek yogurt brand share over all purchase events during which the brand was available in the shopping trip. Those simulated brand shares are calculated for both the multi-consumption learning model with inertia and the one-shot learning model. To predict brand share in the absence of learning for Greek yogurt, I run the same simulation with the estimated true match values, price coefficient and other utility parameters. The initial perception bias is set to 0, assuming households have full information about their true tastes for Greek yogurt.

Table 2.4. Effect of Learning on Greek Yogurt Market Shares

	Predicted share from multi-consumption learning model			Predicted share from one-shot learning model		
	(1) Learning	(2) No learning	(3) % Change	(4) Learning	(5) No learning	(6) % Change
Fage	0.73%	26.17%	3,508%	0.92%	4.26%	364%
Chobani	2.65%	9.58%	262%	3.24%	9.51%	193%
Dannon Greek	1.64%	8.47%	415%	1.91%	5.82%	204%
Yoplait Greek	3.19%	6.16%	93%	3.38%	4.52%	34%

The table compares Greek yogurt brand shares when learning presents versus when it does not. The predicted brand share for each brand is from shopping trips during which the brand was available in the store. Therefore they differ from the observed choice shares in all shopping trips.

Table 2.4 reports those simulated shares of each Greek yogurt brand in trips during which it was available. Columns (1) and (4) show the simulated shares when learning is considered. The prediction from the two models are similar, with a slightly smaller share for each brand from the multi-consumption learning model. Moving to the results from the simulation without consumer uncertainty in columns (2) and (5), we observe a striking increase in choice share for all brands, suggesting the important role of uncertainty in household purchase of Greek yogurt. In addition, the predicted brand shares from the multi-consumption learning model are higher than those from the one-shot learning model.

Although the predicted shares for all Greek yogurt brands are substantially larger when consumers know their true preference, the percentage changes vary significantly by brands. In the multi-consumption learning model, when uncertainty is removed, Dannon Greek increases its share by more than 400%, followed by Chobani with an over 200% increase. Yoplait Greek, however, shows an increase of only 93%, less than one-fourth of the increase for Dannon Greek. Similarly, in the one-shot learning, the share increase of Yoplait Greek is much smaller than the other two brands. In fact, columns (1) and (4) show the simulated share of Yoplait Greek is the highest when uncertainty is modeled. In spite of a positive change, the predicted share of Yoplait Greek becomes smaller than Chobani and Dannon Greek in the absence of uncertainty.

The simulated market share for Fage is less than 1%. However, Fage increases its share by $3,508\%$ in the multi-consumption learning simulation when uncertainty is removed. This dramatic increase can be caused by the fact that the estimated true match value of Fage is from a very small subset of households who ever purchased Fage. In my data period, the majority of the households had never bought Fage. The observed choice probability of Fage is only 0.73% in trips during which it was available, much smaller than other brands.

When I run the simulation, I apply the true match value of Fage, which is the largest among all brands based on column (5) in Table 2.3, to all purchase events during which it was in store. The large predicted market share is generated by this large estimate from very few households.

2.5. Conclusion

In this chapter, I investigate the impact of learning on the market share of Greek yogurt brands. I estimate a yogurt demand model that considers both learning and choice inertia. Households are assumed to be myopic and heterogenous in brand preference and price sensitivity. The estimation results show evidence for learning in Greek yogurt purchases.

In a simple simulation experiment, I compare the predicted brand shares when learning exists versus when it does not. The results show a substantial increase in Greek yogurt market shares in the absence of learning. Although the share of all Greek yogurt brands is significantly higher when uncertainty is removed, Yoplait Greek increases its share much less than other brands, whereas Dannon's share increase is even larger than Chobani. When consumer have no uncertainty towards Greek yogurt, Dannon Greek captures a larger share than Yoplait Greek and the gap between it and Chobani becomes smaller.

Through the analysis, I make various assumptions for the learning process. By relaxing those assumptions, this chapter can be extended in multiple directions. First, I assume households are myopic instead of forward-looking. By allowing forward-looking behavior, the chapter can be extended to the dynamic choice framework. Second and more interestingly, correlated learning might be worth to considering in the context of this study. Whereas inertia always favors existing brands, learning can have the opposite effect when multiple brands share common attributes that need to be learned. Because all those products are marketed as Greek yogurt, a distinct subcategory of traditional yogurt, consumption of one brand can not only reveal the specific brand preference, but also the preference for the shared product attributes, namely the thick, creamy texture and high protein content of Greek yogurt. In this case, learning has spillovers. For example, consumers who like Chobani are more likely to purchase new Greek yogurt of other brands because they may attach a higher value for all Greek yogurt before the actual consumption. If this is the case, the late entry of Dannon and Yoplait can be beneficial.

Conducting other simulation experiments would also be interesting. For example, the counterfactual in which Dannon and Yoplait enter earlier into the choice set can show the impact of entry timing. However, this simulation cannot avoid making complex assumptions on the supply side. For example, if Dannon and Yoplait entered in 2009, would they have had different entry strategies, and how would this timing have affected Chobani's expansion strategies? With a supply side model that incorporates firm action and competitive response, we can explore the effect of entry timing in the Greek yogurt category.

CHAPTER 3

Effect of Incumbent Entry on Chobani's Store Sales

The two large category incumbents Dannon and Yoplait introduced Greek yogurt in 2010 when Chobani had been expanding across stores for two years, reaching a distribution coverage of 40% in $\%ACV$ in Nielsen retailer stores. The subcategory entry of big incumbents added to the varieties of Greek yogurt that compete with Chobani directly. With increasing competition, sales of Chobani should drop in stores that incumbents entered. However, by the time of Dannon and Yoplait's entry, Greek yogurt was a developing subcategory with novel features that were still new to many consumers. The entry of big brands can lead to subcategory expansion that may affect Chobani positively. The positive spillover can occur through increasing subcategory awareness, encouraging consumer sampling and re-purchases, etc. Considering the ambiguous effects just discussed, it is worthwhile to examine how the store sales of Chobani respond to the subcategory entry of Dannon and Yoplait empirically.

In January 2010, Dannon and Yoplait launched their first Greek yogurt products, branded as Dannon Greek and Yoplait Greek, respectively. In many of the stores Dannon and Yoplait entered, Chobani had already been on shelves for a while. With the introduction of new Greek yogurt varieties, consumers had more choices to purchase from the Greek segment. Given the great success of Dannon and Yoplait in regular yogurt, Greek yogurt products from them can be strong competitors of Chobani. Therefore, the standard competition model will predict that Chobani loses sales due to the increased competition. However, this prediction is probably true assuming that the market is mature, a condition not applicable in the current empirical setting.

Greek yogurt, at the time of Dannon and Yoplait's entry, was nonetheless a growing subcategory with very few brand offerings. Many consumers had never purchased Greek yogurt and may not even have been aware of the existence of Greek yogurt generally or Chobani specifically. Product launch from big brands can expand the subcategory aisle and increase sub-segment awareness. Considering the large base of loyal consumers Dannon and Yoplait accumulated over years, new product launches from the two big brands could cause the attention of more consumers than a small entrant that was newly introduced to shelves like Chobani.

Moreover, store promotion and other related marketing activities are also factors that can drive subcategory awareness. Chobani or other existing Greek yogurt brands were rarely featured in stores in 2010. When Yoplait launched its Greek yogurt, the brand had much more frequent store features than other products in the segment. Such promotional marketing activities can not only increase awareness of the featured brand, but introduce consumers to the novel features of Greek yogurt, which may benefit other brands that share the same product characteristics.

Additionally, purchase related spillovers can also occur from consumer sampling and trials. Consumers who tried the new Greek yogurt from Dannon and Yoplait may continue buying from the Greek yogurt segment, consequently increasing the purchase probability of Chobani as well. This possibility is more likely to be true when consumer purchase involves learning and choice inertia, two behavior characteristics that have been frequently documented in the packaged good categories by previous work (e.g., Ackerberg, 2003; Dubé et al., 2010).

Because Dannon and Yoplait did not launch their products into all the stores that Chobani had previously entered, comparing sales of Chobani in incumbent entered stores with sales in non-entered stores prior and post allows me to study whether the entry effect is positive or negative. Moreover, although the two incumbents launched Greek yogurt nationally at the same time, they differred in the number of markets and stores entered. In particular, Yoplait entered into many markets and stores at the beginning of 2010, whereas Dannon took a slower pace and did not enter into many stores until 2011. In addition to that, Yoplait adopted a lower price than competitors and its Greek yogurt was made by adding milk concentrate instead of from a straining process, the standard procedure of producing Greek yogurt used by Chobani and Dannon. The impact on Chobani's sales may also vary accordingly to the price and product difference between Dannon and Yoplait Greek yogurt. By leveraging the resulted variation in the presence and number of new competitors Chobani faced due to the different entry strategies of Dannon and Yoplait, I am able to study the heterogenous entry effect as well.

The rest of this chapter is organized as follows. First, I discuss the past literature related to this study in the next section. Then I describe the data construction and introduce my empirical model. After a detail discussion of the model specification, I then present the empirical results from model estimation. Finally, the last section concludes my findings.

3.1. Related Literature

There is extensive literature on the effects of competitive entry.[1] Many of these previous studies focus on the existing competitors' reaction to new entrants, such as price and quality adjustments. For example, several studies explore the entry effect on prices from chain store entry (e.g., Basker and Noel, 2009; Jia, 2008; Bennet and Yin, 2019). This chapter differs from previous literature by examining the impact on market outcome instead of firms' competitive reaction. Price reaction is not considered because I do not observe changes of shelf price or promotion activities from Chobani in reaction to the competitors' entry. In fact, Chobani was a small firm facing supply constraints and did not have the capacity to react to the entry of Dannon and Yoplait.

Another stream of related work studies the spillover effect that has been documented for both non-competing brands in the context of umbrella brands or line extensions and among competing brands in the same product category. This study is related to the latter. For example, Janakiraman et al. (2009) investigate the mechanism of positive spillovers between competing brands in the pharmaceutical industry. Their empirical setting is similar to the current study in the context that competing brands enter into market sequentially. They focus on whether and how the perceptions of the first brand spill over to the later entrants. Using consumer choice data, they find that customers' quality beliefs about the first entrant can influence customers' prior beliefs about the quality of later entrants. And such second mover advantage occurs only when the products from competing brands are

[1] I use the term store entry, instead of retailer adoption decision of new yogurt brands for the following reasons. First, Dannon and Yoplait did not have Greek yogurt products before. Their introduction of Greek yogurt in 2010 is an entry to the subcategory. Second, as two largest national brands in the category, Dannon and Yoplait gain shelf access for their new products very easily. Lastly, since Chobani and Greek yogurt were getting popular in 2010, retailer stores were expanding yogurt shelves and were likely to stock more Greek varieties, especially products from large brands.

similar. Different from their work, in this chapter, I investigate whether there is positive spillover for the existing brand when new competitors enter the subcategory.

Anderson and Simester (2013) study the impact of competitors' advertising on sales at a private label retailer in a large-scale randomized field experiment. They show evidence of large positive spillovers, with competitors' advertisements causing an increase of more than 4% for items ordered by customers in some categories. Competitors' advertising may prime customers to think about the category and invoke a purchase need that later can be fulfilled by a preferred retailer not necessary the one advertised. Further comparing the variation of these positive spillovers across customers and product categories, they also illustrate the important moderating role of product standards, customer learning, and switching costs. We can expect these documented behavior mechanisms occur in the current empirical setting. Consider a consumer who shops in a store where Yoplait Greek is featured. If the store feature of Yoplait Greek invokes the purchase intention of Greek yogurt, the consumer will decide which brands to buy only within the Greek segment. The probability of purchasing Chobani is then larger than if the consumer did not consider buying Greek yogurt.

Negative spillovers among competing brands have been documented mostly in behavior literatures. Roehm and Tybout (2006, 2009) use a lab experimental setting to demonstrate how a product scandal from one brand can adversely affect the category and competing brands. A related example to their study is how the recall of Vioxx, a painkiller that was forced to be withdrawn from the market due to safety concerns, damages the competing brand Celebrex. Similarly, Dark and Richie (2007) illustrate the negative consequences of a deceptive advertising from a competitor and how it can affect consumers' subsequent response to firms that are unrelated to the original deception.

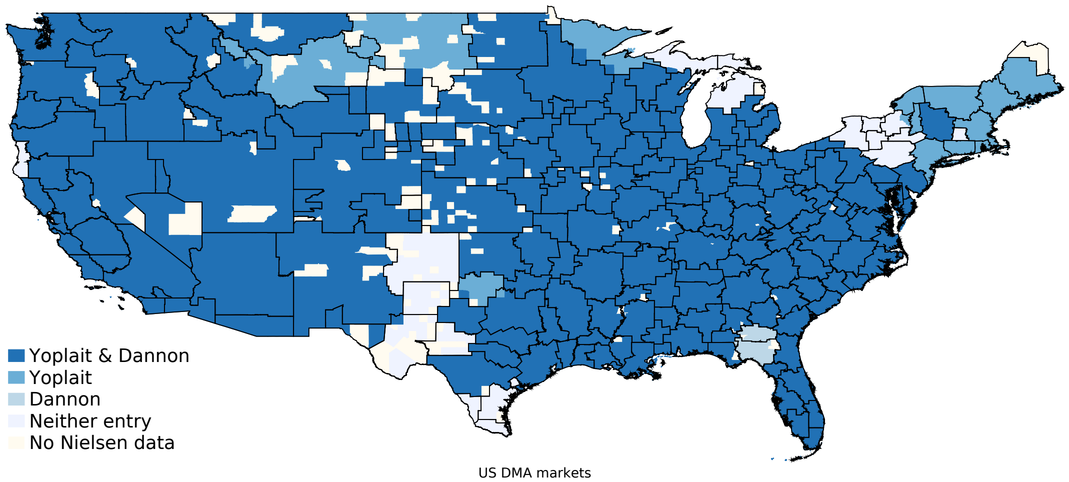
Yoplait Greek was made using milk protein concentrate to get a thick texture and high protein content. While milk protein concentrate is not among the permissible ingredients of yogurt as set forth under the FDA, a law suit was filed that claims that Yoplait Greek should not be labeled as Greek yogurt, or even yogurt. Although this law suit came late in 2011, consumers might have been able to recognize the poor quality of Yoplait Greek. Bad experiences from consuming Yoplait Greek can lead to negative perceptions towards other Greek yogurt, destroying the reputation of the subcategory and thus affecting Chobani negatively. The adverse impact from bad consumption experience may even be exaggerated by the high prices of Greek yogurt, which tends to cost twice as much as regular yogurt. This possibility is particularly likely for new consumers who have had none or few consumption experiences of Chobani or other brands of Greek yogurt.

3.2. Data and the Empirical Model

In Nielsen retail stores, sales of Yoplait Greek yogurt are first observed at week 3 in 2010, and sales of Dannon Greek one week later. The store entry time of each brand is defined as the first week with observed sales. In contrast with region-by-region sequential roll-outs observed for Chobani, the two incumbents introduced their new products in many regions concurrently. Figure 3.1 shows an entry map of Dannon and Yoplait Greek yogurt in the first two quarters of 2010 at DMA market level. A DMA market is considered to be an entered market of a brand if sales of the brand are observed in at least one store in the market. Based on this definition of market entry, Dannon and Yoplait Greek yogurt appeared almost everywhere.

The sprinkler entry covered many geographic areas, but not every store within a market. Instead, I observe phased entry patterns across stores, with two big entry waves from 2010

Figure 3.1. Market Entry of Dannon and Yoplait in Q1 & Q2 of 2010



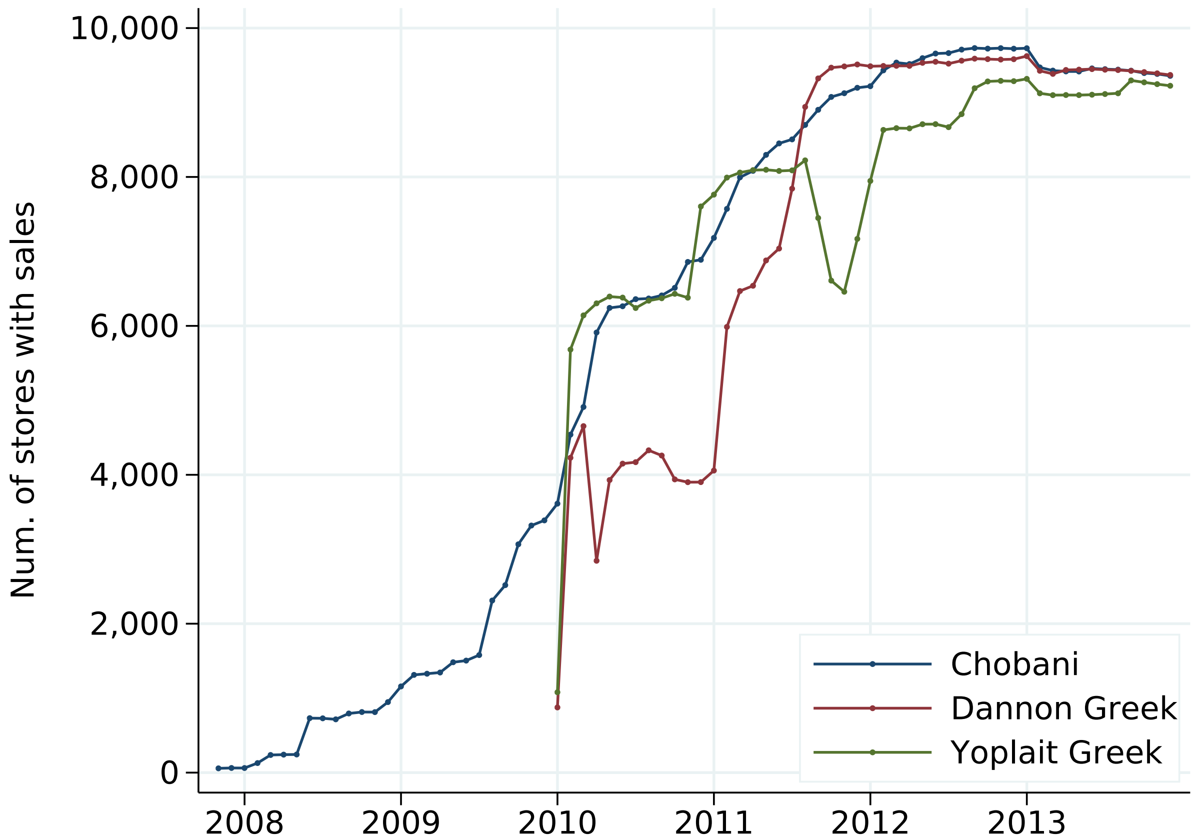
This figure plots the DMA market entry of Dannon and Yoplait Greek yogurt. If the brand was available in at least one store by the end of the second quarter in 2010, the market is considered an entered market of the brand.

through 2011. This pattern can be seen in Figure 3.2. The first wave of store entry occurred at the beginning of 2010, which marks the initial launch of Greek yogurt from the two brands. Yoplait's entry is massive, appearing in more than half of the stores in my data. Shortly after entry, Yoplait Greek yogurt appeared in more stores than Chobani. Dannon, on the other hand, not only began with much fewer stores, but exited from some stores after entry.[2]

After the initial launch, store entry of Dannon and Yoplait slowed down as Figure 3.2 shows that the number of stores selling each brand became constant. Yoplait started the second round of store entry near the end of 2010, followed soon by Dannon. Compared to the initial entry in 2010, the second wave of store entry is more progressive, especially Dannon's entry which is almost linear in time. Figure 3.2 shows that the roll-outs of all three brands in Nielsen retailer stores continued until the end of 2011 when Greek yogurt appeared in almost all the stores.

[2]An interview with industry experts reveals that the temporary store exist of Dannon Greek is due to the supply constraint of limited capacity in massive production of Greek yogurt.

Figure 3.2. Store Entry of Greek Yogurt Brands



This figure plots the number of stores selling each of the three Greek yogurt brands at monthly level from November 2007 to December 2013. The data is from stores in food channel that reported yogurt sales to Nielsen every year from 2007 to 2015.

In this study, I only consider the entry of Dannon and Yoplait in stores that had been selling Chobani before 2010. For this set of $3,144$ stores, I investigate the sales response of Chobani to the subcategory entry of the two incumbents. Furthermore, I restrict attention to the early entry of Dannon and Yoplait in the beginning of 2010 (i.e., the first entry wave). Only stores with previous Chobani presence are chosen because I need to observe the pre-entry data to identify the sales changes caused by the entry of incumbents. The primary reason for focusing only on early entries is to avoid identification problems due to potential spillovers across stores. Consider, for example, a store entered by Dannon at week 30 in 2010. The sales of Chobani in this store before Dannon's entry were probably already affected by the nearby stores that Dannon entered earlier. This is a problem to identification if Dannon's entry decision to this store is based on how many nearby stores it already entered, which is very likely to be true given that yogurt distribution is direct store delivery. If so, the pre-entry period Chobani sales for a store with late Dannon entry will be contaminated. Thus a pre-post comparison will provide misleading results of Dannon's entry impact.

In particular, my selection of early entry stores includes those with entry of at least one incumbent before week 12 in 2010. About 78% of store entries from Dannon and Yoplait in 2010 happened before week 12, while entries in the rest of 2010 are patchy. Other than for this reason, the choice of the first 12 weeks is rather arbitrary and this filter is used to select the earliest entries of Dannon and Yoplait for the reasons discussed above.

In total, I observe $6,754$ early entry stores, among which $2,792$ stores were entered by Chobani before 2010 and will be referred to as "entered stores" hereafter. The rest of the early entry stores are excluded from my analysis because Chobani entered those stores after 2010 and we observe no or few store sales of Chobani before the entry of Dannon or Yoplait.

One observation from Figure 3.2 is that the number of stores selling Dannon Greek yogurt dropped after its store entry. Further investigation of the data and an interview with industry experts reveal that this drop is due to Dannon's limited capability in massive production of Greek yogurt, rather than data recording errors.[3] To minimize the supply side noises, I

[3]There is also a drop in the number of stores selling Yoplait Greek yogurt around the second quarter of 2011. Since my analysis does not cover this time period, I will not further discuss this issue. However, investigation of the data shows that the missing store sales are more likely to be a distribution issue, i.e., Yoplait discounted its products in some stores, rather than store recording errors.

remove stores with less than 5 weeks of Yoplait Greek or Dannon Greek yogurt sales in the first 10 weeks since store entry, resulting in a sample size of $2,484$ entered stores.

Throughout the analysis, I consider three entry events: Dannon entry, Yoplait entry, and both incumbents entry. The analysis for each entry event runs separately by comparing Chobani's sales in the entered stores with sales in a control sample. In the Dannon entry event, the entered sample includes 118 of stores that Dannon entered and Yoplait did not enter in the sample period. Analogously, the Yoplait entered stores are those entered only by Yoplait, consisting of 882 stores in total. In the both incumbents entry event, I consider joint entry of Dannon and Yoplait, which is defined as a store entry time gap between the two brands of no longer than two weeks. Stores entered by both brands before week 12, but with larger entry time differences are excluded from the data. The sample size for the both incumbents entry event is $1,352$.

While the entered sample is specific to each entry event, the control sample for the three entry events is the same. It includes 348 Chobani stores that neither Dannon nor Yoplait entered by week 32 in 2010, which is the end of analysis period.

My analysis time period expands 52 weeks, including the last 20 weeks in 2009 and the first 32 weeks in 2010. Since all the three entered samples include stores with incumbent entry before or at week 12, the post-entry period in each store includes at least 20 weeks. I discard data after the 20^{th} week since entry so that all entered stores are observed for the same time length in the post-entry period. The length of pre-entry period for an entered store varies from 23 to 32 weeks depending on the time of the incumbent entry.

To estimate the impact of incumbent entry on Chobani's store sales in each entry event, I use a differences-in-differences approach to exploit the panel structure of the data.[4] The dependent variable is log volume sales in ounces, which I denote as $log(y_{it})$, the log sales of Chobani in store i at week t. The base specification I estimate is

$$log(y_{it}) = \alpha_i + \lambda_t + \delta IncumbentPost_{it} + \theta X_{it} + \epsilon_{it}\,. \tag{3.1}$$

In Equation 3.1, $IncumbentPost_{it}$ is a dummy variable that is equal to 1 if store i is an incumbent entered store and week t is in the post-entry period. The coefficient of $IncumbentPost_{it}$, δ, is the entry effect, the primary variable of interest. I assume a homogenous entry effect in the model. It can be interpreted as a weighted average of entry effect across all entered stores and all periods in an entry event.

The variable X_{it} is a vector of control variables that are store and time specific. First, I include log weekly store prices for Chobani and its major competitors, to control for the changes in sales due to price variation. Since the specification is a log-log model, the price coefficients are the own and cross-price elasticities, measuring the substitution pattern between Chobani and other yogurt brands. The second set of control variables in X_{it} includes the number of Chobani UPCs sold in the store, a dummy variable of store feature (equal to 1 if Chobani is featured in the store at week t), and the total volume sales of all other yogurt except Chobani. Those variables are also constructed by store and week, in order to capture the variation from product availability, store promotion, and shocks to the yogurt category at a specific week in the store. Lastly, store assortment of yogurt can also have an

[4]In each entry event, the incumbent entry time varies across stores. This setting is a special case of the general differences-in-differences set up. Researchers often refer to such settings as event study design, or staggered adoption design. For a detail discussion of estimation and inference in this setting, see Athey and Imbens (2018).

influence on Chobani sales as consumer purchases are constrained by the products available on shelves. Therefore, I control for store assortment adjustments by including the maximum number of UPCs with observed sales in a month at each store, separately for regular yogurt, Chobani and all other Greek yogurt.

The model is a two-way fixed effects design with control for both store and time fixed effects. The variable α_i captures the mean difference in Chobani sales level across stores. And λ_t controls for time specific sales shocks common to all stores. The last term in Equation 3.1, ϵ_{it}, captures the i.i.d. random shocks that are unobserved in the data. I use Huber-White SEs clustered at the store level to allow for arbitrary correlation of ϵ_{it} within each store.

In applying the differences-in-differences framework to the data, it is important to consider carefully the "experiment" created by the event, which is Dannon and Yoplait's entry to the Greek yogurt subcategory in this study. In the ideal scenario, Dannon and Yoplait would choose which store to enter randomly. Both the entry decision of the two brands and the store adoption decision would be independent of Chobani's store sales. If so, the model I employ in Equation 3.1, if correctly specified, would provide an unbiased estimate of average entry effect. Unfortunately, the present empirical setting is very likely to differ from the ideal case. For example, one strong piece of evidence against random entry is that in early 2010 Dannon did not enter into any stores in the New York market which is the first market Chobani entered and which had the largest store coverage rate and market share of Chobani at the time of Dannon's entry. The Dannon entered stores are those stores Chobani entered in the last two quarters of 2009. Compared with many control stores with a long presence of Chobani, the entered stores are very likely to have a different sales growth trend of Chobani. As a result, the model specified in Equation 3.1 violates the identifying assumption of differences-in-differences framework, and thus cannot identify the impact of Dannon's entry on Chobani's sales.

A possible way to improve the identification is to modify the time fixed effect in Equation 3.1. Assuming a common time trend to all stores is a very strong assumption in the present empirical setting. As a new startup in the US yogurt market, Chobani did not have the production capacity or distribution power to enter into all markets simultaneously. In fact, it entered into many markets in the Northeast in 2008, but did not appear in any markets on the west coast until late 2009. By the time of Dannon and Yoplait's entry, both sales level and market share of Chobani varied largely across DMA markets depending on the entry timing and number of stores it entered. More importantly, sales of Chobani were probably growing at different rates in different markets. Considering such differences, if Dannon and Yoplait chose to enter markets with slow Chobani growth rates and to avoid markets where Chobani develops faster, or vice visa, then the entered stores and the control stores will not have the same sales growth rate after controlling for a common week fixed effect. To solve this problem, I replace the variable λ_t with $\lambda_{m_i t}$, where m_i indexes for the DMA market where store i operates. Thus $\lambda_{m_i t}$ is the DAM-by-week fixed effect that captures any differences in Chobani growth rate across markets.

In addition, I observe large variation in Chobani entry timing across stores within the same DMA market. Rather than entering most stores in a market concurrently, Chobani became available in many stores a long time after it first appeared in some stores in the same market. Consequently, stores in the same market vary in week-by-week sales growth rate. We can expect a store that recently adopted Chobani to have a very different sales trajectory compared with another store that had been selling Chobani for weeks or quarters. Controlling for market specific week fixed effect fails to capture such differences in time series change across stores. The estimated entry effect will still be biased if the entered stores differ from control stores in sales growth rate even from the pre-entry period.

In order to address this concern, I include a linear function of time that is specific to each store. In particular, I estimate the following model

$$log(y_{it}) = \alpha_i + \lambda_t + \gamma_i t + \delta IncumbentPost_{it} + \theta X_{it} + \epsilon_{it} \,. \tag{3.2}$$

The term $\gamma_i t$ in Equation 3.2 is an additional control of the differences-in-differences model. It is a store specific coefficient γ_i multiplying the time trend variable t (i.e.,week in this study). It is a specification adopted by previous literature with similar differences-in-differences design (e.g., Autor, 2003; Besley and Burgess, 2004). The identification of entry effect in Equation 3.2 comes from whether the entry of Dannon Greek or Yoplait Greek leads to deviations from pre-existing store specific trends. Note that since most stores are observed for multiple weeks in the pre-entry period, the model should be able to separate the store trends and the entry effect.

Including a store specific linear time trend could capture differences in sales growth rate across stores in a limited and potentially revealing way. The remaining concern is whether the linear form of time trend is sufficient enough to capture the potential pre-entry trend. I will not explore more flexible forms of store specific dynamics by allowing for quadratic or polynomial time slopes. Instead, I investigate this issue later with a parallel trend test following the differences-in-differences estimation for each entry event analysis.

3.3. Model Estimation Results

In this section, I present the empirical model estimation results for each entry event and investigate the identifying assumption of the differences-in-differences model through a parallel trend test.

3.3.1. Yoplait Entry Event

The regression results in the Yoplait entry event are shown in Table 3.1. Each column presents a regression of log Chobani volume sales on the $IncumbentPost$ dummies, store and time fixed effects. Columns (2)-(5) include control variables X_{it} and columns (4) and (5) also control for the store specific time trend.

The first two columns show results from the model with week fixed effects. The coefficient of $IncumbentPost$ is positive in column (1) when only controlling for store and week fixed effects, indicating on average there is a positive change on Chobani sales from the entry of Yoplait Greek. However, this impact is estimated imprecisely because it does not include any of the control variables in X_{it}. Column (2) adds all those controls and reports a coefficient of -0.175, suggesting Yoplait's entry reduced Chobani store sales by approximately 17%. In column (3), I replace the week fixed effect with DMA market by week fixed effect. The point estimate of Yoplait's impact increases to -0.076. The change in the $IncumbentPost$ estimate from columns (2) to (3) suggests the sales growth rate of Chobani in Yoplait entered markets differed from the growth rate in non-entered markets. Considering the market specific time shocks is important and neccessary.

Column (4) addresses the differences in the sales growth rate across stores in the same market by including store specific time trends. And it is the preferred model. Compared

Table 3.1. Yoplait's Entry Effect on Chobani

Model	(1)	(2)	(3)	(4)	(5)
IncumbentPost	0.170***	-0.175***	-0.076***	-0.020	0.036***
	(0.017)	(0.016)	(0.019)	(0.013)	(0.013)
log(price) Chobani		-2.990***	-2.973***	-2.961***	-3.018***
		(0.035)	(0.040)	(0.039)	(0.045)
log(price) Dannon		0.333***	0.326***	0.247***	0.261***
		(0.019)	(0.020)	(0.017)	(0.018)
log(price) Yoplait		0.147***	0.087***	0.016	0.047***
		(0.015)	(0.016)	(0.014)	(0.014)
log(price) other regular yogurt		-0.111***	-0.177***	0.071**	0.154***
		(0.029)	(0.033)	(0.028)	(0.030)
log(price) other Greek yogurt		0.189***	0.170***	0.254***	0.294***
		(0.032)	(0.031)	(0.026)	(0.028)
Num.of Chobani UPCs		0.114***	0.116***	0.119***	0.076***
		(0.005)	(0.005)	(0.005)	(0.004)
Store feature		0.123***	0.080***	0.083***	0.080***
		(0.011)	(0.011)	(0.011)	(0.013)
Sales of other yogurt		0.268***	0.276***	0.219***	0.258***
		(0.025)	(0.025)	(0.024)	(0.030)
Assortment Chobani		-0.017***	-0.001	-0.005	0.009**
		(0.004)	(0.005)	(0.004)	(0.004)
Assortment regular yogurt		-0.005***	-0.002***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.001)
Assortment other Greek yogurt		0.004**	0.000	-0.003*	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Store effects	Y	Y	Y	Y	Y
Week effects	Y	Y			
DMA-week effects			Y	Y	Y
Store time trend				Y	Y
R^2	0.95	0.95	0.96	0.97	0.96
Adjusted-R^2	0.94	0.95	0.96	0.97	0.96
Num.of observations	54,510	54,510	54,510	54,510	39,945

Huber-White robust SEs clustered at store level are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Columns (1)-(4) show the results from the full sample, and column (5) reports results from a subsample.

with column (3), the coefficient of $IncumbentPost$ remains negative, but becomes smaller in magnitude and statistically insignificant. It suggests the entry of Yoplait Greek had no significant impact on Chobani's store sales.

In column (5) of Table 3.1, I report results from the same specification as in column (4) from a subsample of data. The subsample is selected by removing stores Chobani entered in the first 20 weeks after its initial market entry or in the last 20 weeks of 2009. I exclude those stores due to the concern that sales growth in very early or recent Chobani stores might have unique patterns that the simple linear store trend cannot capture. The estimated effect of Yoplait's entry in column (5) is 0.036, a positive and significant number that indicates Chobani sales increased by approximately 4% in Yoplait entered stores.

As discussed earlier in the chapter, the identifying assumption of the above differences-in-differences approach is that sales of Chobani in the control stores in a given week serve as the valid counterfactual for the sales that would have been realized in the entered stores in the absence of Yoplait's entry. Unfortunately, we cannot observe or test this assumption directly, because we do not observe the counterfactual results. However, since my sample includes many weeks for a store, I can run a causality test on pre-entry periods in the spirit of Granger (1969) to examine whether the growth trends of Chobani sales between Yoplait entered stores and non-entered stores are the same prior to the entry of Yoplait Greek. If the trends are similar between the entered and non-entered stores in the pre-entry period, we have further assurance that the sales in non-entered stores are a valid counterfactual of sales in entered stores in the post-entry period.

To test the pre-entry trend, I estimate the base model augmented with leads and lags of entry dummies. In this model, if entry is independent of the pre-entry period trend, the sales of Chobani at time t should not be affected by the entry of Yoplait that occurs at the future time $t + \tau$. In particular, I use the following model I use to test the pre-entry period trend

$$log(y_{it}) = \alpha_i + \lambda_t + \gamma_i t + \sum_{\tau=0}^{m} \delta_{-\tau} Entry_{i,t-\tau} + \sum_{\tau=1}^{q} \delta_{+\tau} Entry_{i,t+\tau} + \theta X_{it} + \epsilon_{it} \,. \tag{3.3}$$

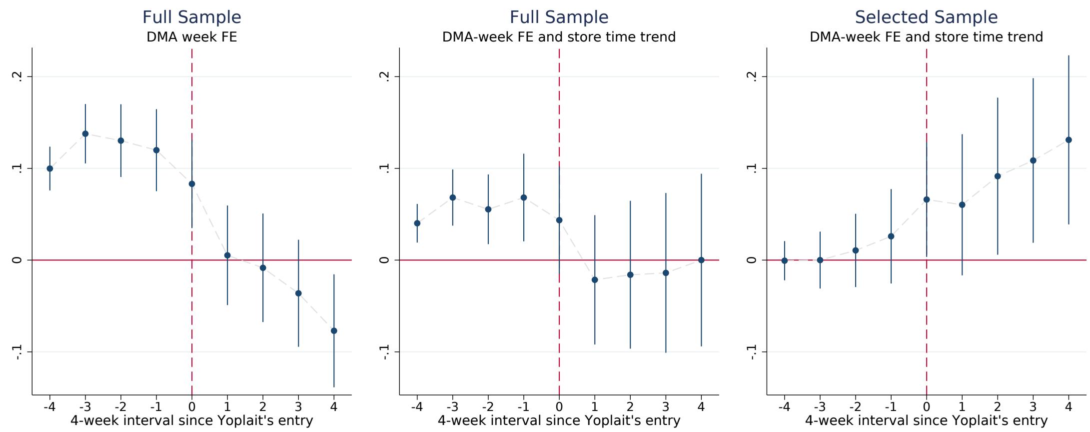
Instead of a single dummy variable $IncumbentPost_{it}$, Equation 3.3 allows for m lags and q leads. The dummy variable $Entry_{i,t-\tau}$ is an indicator for whether store entry of Yoplait occurred τ weeks before the current week t, and likewise, $Entry_{i,t+\tau}$ indicates for whether the Yoplait entry would occur τ weeks after. Therefore, the coefficients on entry lags are the post-entry effects, and the coefficients on entry leads are the anticipatory effects. A test of the differences-in-differences assumption is $\delta_{+\tau} = 0$; that is, the coefficients on all leads of the entry should be zero. Moreover, the pattern of lagged effects is of interest too because they show the dynamics in entry effects. For example, if $\delta_{-\tau}$ is increasing in $\tau = 0, 1, ...m$, the entry effect of Yoplait accumulates over time.

This specification is similar to the Granger causality model. Autor (2003) and Deshpande and Li (2017) use this approach to test the differences-in-differences assumption. I employ the parallel-trends test by creating entry lead and lag dummies at a four-week interval instead of one-week level to reduce noises arising from a particular week. Because a store is observed for at most 52 weeks, the data are divided into 13 such four-week intervals. An entry dummy $Entry_{i,t+\tau}$ is equal to 1 if Yoplait entered the store at the τ^{th} week interval after the current week interval. The test is applied to column (3) to column (5) in Table 3.1 by replacing the $IncumbentPost$ dummies with entry leads and lags.

The coefficients of entry dummies are depicted in Figure 3.3. The plot on the left shows the coefficients in the full sample regression with DMA by week fixed effect. All the entry leads are shown to have large and positive coefficients. This result suggests Chobani sales were higher in entered stores than in the control stores before Yoplait Greek entered. Controlling for store trend reduces the size of pre-entry trends as shown in the middle plot. However, the entry leads coefficients remain positive, providing evidences of an anticipatory response in the Yoplait entered stores, a violation of the parallel-trends assumption between entered stores and control stores from the pre-entry period. Hence, the estimated impact of Yoplait entry from columns (3) and (4) are not trustworthy. The plot on the right, however, shows a different pattern, with all coefficients of entry leads being insignificant from zero. This pattern is from the selected sample that excludes stores Chobani entered very early and recently. The coefficients on the first two leads are extremely close to zero, whereas a slightly upward yet insignificant trend is observed in stores right before Yoplait Greek entered them. This pattern provides confidence that the estimated positive effect in column (5) is more reliable than the estimates in the other four columns.

Although the coefficients of the last two leads before Yoplait's entry are close to zero and insignificant, the subsequent continuously growing pattern of entry dummy coefficients brings up the suspicion that some uncontrolled factors drive the sales growth of Chobani in entered stores, rather than Yoplait's entry. To address this concern, I adopt a matching method and run the analysis only on the matched sample. The matching is based on Chobani's sales growth rate prior to Yoplait's entry. In particular, I calculate the sales growth rate of Chobani from the second quarter to the last two quarters in 2009, and then rank all stores based on this variable. Each entered store is matched to a control store with the closest level of growth rate. I first search for a control store within the same DMA market of the

Figure 3.3. Yoplait Effect: parallel trend test

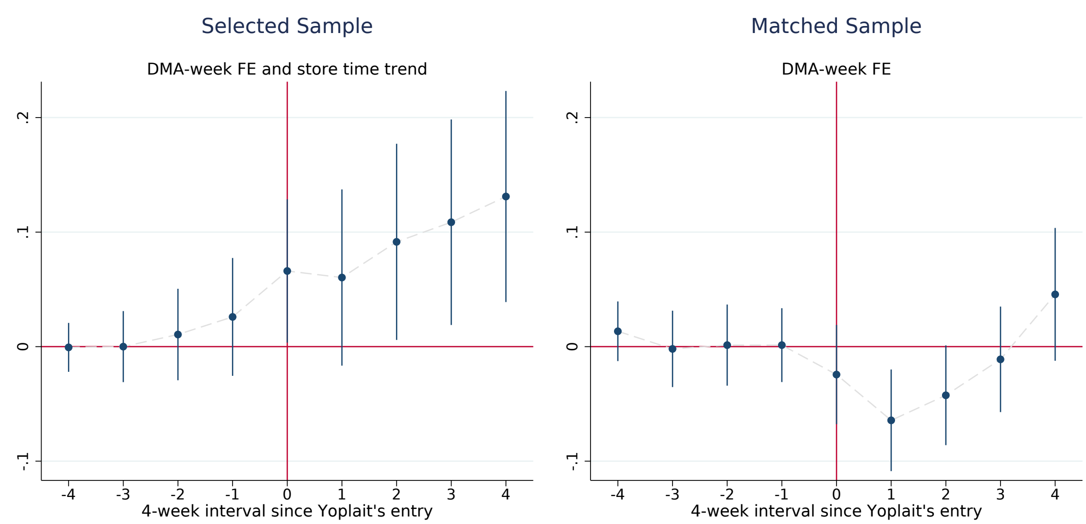


This figure plots the estimated coefficients and 95% confidence intervals for the entry leads and lags from the parallel-trends test. Yoplait Greek entered at week interval 0, marked by the red dashed line in each plot. The coefficients to the left of the red dashed line are the estimated anticipatory effects, and coefficients to the right show the post-entry dynamics.

entered store. If no match exists or the difference between the matched pairs is too large, I continue to search for stores in the same state, and then stores within the same region, which is defined by Nielsen. To avoid a poor match, I discard matched pairs with large distance in the pre-entry growth rate. Therefore, I exclude some entered stores from the matched sample if they do not receive a good match. The described matching method is a 1:1 nearest-neighbor matching with replacement. A control store appears in the matched sample only if it is matched to one or more entered stores. In the matched sample analysis, each control stores receive a frequency weight that reflects the number of times it is selected as a match.

After matching, I apply the differences-in-differences model to the matched sample. Because the purpose of applying the matching mechanism is to remove differences in Chobani's growth rate across stores, with a good match, the entered stores and the control stores should have a pre-entry parallel trend without controlling for the store-specific time trend. Figure 3.4 compares the parallel trends between the selected sample and the matched sample. Indeed, the result from the matching sample shows no evidence of an anticipatory response even in absence of store time trends. All the coefficients on the four entry leads are around zero. The upward pattern of entry dummies in the selected sample is no longer present in the matched sample. Also notice the pre-entry parallel trend can only hold when controlling for the store-specific time trend, which is a condition no longer needed in the matched sample.

Figure 3.4. Yoplait Effect: parallel trend test from matching



This figure plots the estimated coefficients and 95% confidence intervals for the entry leads and lags from the selected sample and the matched sample. In both plots, Yoplait Greek entered at week interval 0, marked by the red dashed line in each plot. The coefficients to the left of the red dashed line are the estimated anticipatory effects, and coefficients to the right show the post-entry dynamics.

The two plots in Figure 3.4 show some divergence in post-entry dynamcis. Contrary to the positive coefficients of all entry lags in the selected sample regression, the matched sample analysis finds a negative shock immediately after the entry of Yoplait Greek. Chobani sales experienced a sharp drop when Yoplait Greek entered. And the negative shock became even larger in the second four-week interval, and then began to diminish with an upward trend. The Yopalit entry impact became positive over time. A consistent finding from the two plots is that Chobani sales increased a few weeks after Yoplait Greek entered.

3.3.2. Dannon Entry Event

Table 3.2 reports the results of the Dannon entry regression. In column (2), the estimated coefficient of *IncumbentPost* implies a 15% increase in Chobani sales after the entry of Dannon Greek. The estimated impact becomes negative and insignificant as we move to column (3), where the results are from the model controlling for DMA-by-week fixed effects instead of week fixed effects. The addition of store specific trends in column (4) estimates an even larger negative effect, a 24% reduction in Chobani sales after the entry of Dannon Greek.

Contrary to the positive effect estimated in the Yoplait entry case, the results in Table 3.2 suggest sales of Chobani decreased in the Dannon entered stores. Close scrutiny of the data shows that all Dannon entered stores are from the same retailer chain. I also find Dannon did not enter all the stores in the chain. Thus, the chain has both entered stores and control stores, allowing me to apply the differences-in-differences framework just to stores from this chain. Column (5) of Table 3.2 shows the regression results using only the data from the chain. It reports an even larger negative coefficient on *IncumbentPost* dummies. The estimated entry impact is about 6% more reduction in Chobani sales compared to column (4), where I also include control stores outside the entered chain.

Compared to Yoplait's massive entry, Dannon entered into considerable fewer stores and markets. In particular, the markets that Dannon avoided totally are in the Northeast region, where Chobani originated and had the highest store coverage and market shares. The fact

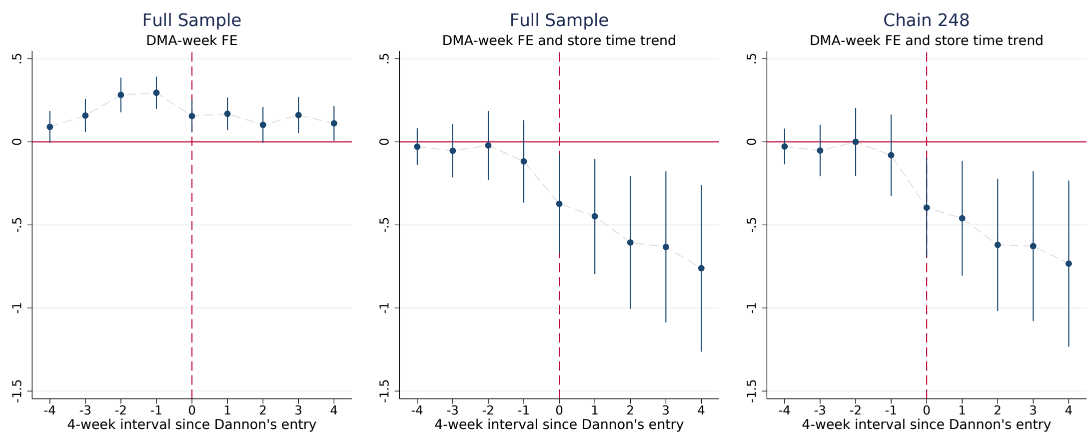
Table 3.2. Dannon's Entry Effect on Chobani

Model	(1)	(2)	(3)	(4)	(5)
IncumbentPost	-0.058	0.142***	-0.010	-0.274***	-0.342***
	(0.047)	(0.024)	(0.033)	(0.042)	(0.046)
log(Price) Chobani		-2.463***	-1.390***	-1.286***	-0.997***
		(0.064)	(0.132)	(0.128)	(0.161)
log(Price) Dannon		0.531***	0.164**	0.184***	0.246
		(0.045)	(0.080)	(0.070)	(0.152)
log(Price) Yoplait		0.080**	0.231***	0.155***	-0.093
		(0.039)	(0.054)	(0.053)	(0.141)
log(Price) other regular yogurt		-0.102**	0.059	0.043	0.037
		(0.044)	(0.060)	(0.055)	(0.093)
log(Price) other Greek yogurt		0.364***	0.197***	0.073	-0.014
		(0.046)	(0.057)	(0.046)	(0.090)
Num.of Chobani UPCs		0.183***	0.21***	0.217***	0.283***
		(0.007)	(0.007)	(0.008)	(0.008)
Store feature		0.071**	0.042	0.037	0.006
		(0.029)	(0.026)	(0.027)	(0.038)
Sales of other yogurt		0.372***	0.262***	0.190***	0.188***
		(0.030)	(0.041)	(0.033)	(0.045)
Assortment Chobani		-0.073***	-0.061***	-0.049 ***	-0.072***
		(0.006)	(0.007)	(0.006)	(0.009)
Assortment regular yogurt		0.000	0.000	0.000	0.002
		(0.001)	(0.001)	(0.001)	(0.002)
Assortment other Greek yogurt		-0.007***	-0.008***	-0.010***	-0.012**
		(0.003)	(0.003)	(0.003)	(0.005)
Store effects	Y	Y	Y	Y	Y
Week effects	Y	Y			
DMA-week effects			Y	Y	
Store time trend				Y	Y
R^2	0.97	0.96	0.97	0.98	0.88
Adjusted-R^2	0.96	0.96	0.97	0.97	0.86
Num.of observations	20,555	20,555	20,555	20,555	9,765

Huber-White robust SEs clustered at store level are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Columns (1)-(4) show the results from the full sample, and column (5) reports results from stores in Chain 248.

that Dannon did not enter into any of the stores in those markets raises the concern that the estimated entry impacts from columns (4) and (5) in Table 3.2 are correlational rather than casual. Consider, for example, that Dannon used Chobani's growth rate as a signal of Greek yogurt demand potential, and selected to enter stores where Chobani grew faster, and if the model I employ fails to control for differences between entered stores and control stores due to such selection, the estimated positive effect is not caused by Dannon's entry, but instead is a direct result of Dannon's selection strategy. To test this possibility, I apply the previous parallel-trends analysis used in the Yoplait case to the Dannon entry event. The results are presented in Figure 3.5.

Figure 3.5. Dannon Effect: parallel trend test



This figure plots the estimated coefficients and 95% confidence intervals for the entry leads and lags. Dannon Greek entered at week interval 0, marked by the red dashed line in each plot. The coefficients to the left of the red dashed line are the estimated anticipatory effects, and the coefficients to the right show the post-entry dynamics.

Figure 3.5 plots the entry leads and lags coefficients and 95% confidence interval from the Dannon entry case. Results are comparable with the Yoplait entry case. The plot on the left shows results from the model without controlling for store trends. The entry leads coefficients are all positive, providing evidence of anticipatory trends in the pre-entry period and thus a violation of the parallel-trends assumption. However, once store time trends are considered, sales growth trends of Chobani between entered and control stores are the same in pre-entry periods, as shown in the other two plots. This finding provides assurance that the positive coefficients in columns (4) and (5) in Table 3.2 are evidence that the entry of Dannon led to an increase in Chobani sales. Moreover, restricting control stores to those from the entered chain improves the pre-entry trend by moving the last entry lead coefficient closer to zero. This finding explains the difference in the $IncumbentPost$ coefficient between column (4) and column (5) in Table 3.2.

Entry of Dannon Greek leads to a sharp decrease in Chobani sales, as shown in the right and middle plots of Figure 3.5. The estimated entry lags coefficients from the two plots have similar patterns. They show the same post-entry dynamics that suggest the negative impact of Dannon Greek tends to accumulate over time.

Matching is less necessary in the Dannon entry event, because Figure 3.5 provides strong evidence that sales growth in entered stores and control stores have parallel trend in pre-entry period. Also, since all stores in the entered sample started to sell Chobani in the last two quarters of 2009, matching on previous Chobani sales is hard because very little data are available. Therefore, I do not perform a matching analysis in the Dannon entry case.

3.3.3. Both Incumbents Entry Event

Table 3.3 shows the results from the both incumbents entry case. The model specifications from columns (1) to (4) are identical to those used in the previous two entry cases. As in the Yoplait entry case, column (5) applies the model to a subsample that removes stores with very early or very recent Chobani entry.

Table 3.3. Dannon and Yoplait's Entry Effect on Chobani

Model	(1)	(2)	(3)	(4)	(5)
IncumbentPost	-0.057**	0.125***	-0.076***	-0.153***	-0.099***
	(0.025)	(0.019)	(0.024)	(0.022)	(0.032)
log(Price) Chobani		-2.008***	-1.731***	-1.630***	-1.871***
		(0.030)	(0.044)	(0.039)	(0.080)
log(Price) Dannon		0.221***	0.058*	0.233***	0.073
		(0.023)	(0.034)	(0.027)	(0.050)
log(Price) Yoplait		0.224***	0.269***	0.250***	0.321***
		(0.024)	(0.033)	(0.028)	(0.048)
log(Price) other regular yogurt		0.135***	0.102***	0.051*	0.032
		(0.034)	(0.036)	(0.027)	(0.053)
log(Price) other Greek yogurt		0.057***	0.022	0.087***	0.071*
		(0.021)	(0.025)	(0.021)	(0.037)
Num.of Chobani UPCs		0.275***	0.285***	0.276***	0.265***
		(0.004)	(0.004)	(0.004)	(0.008)
Store feature		0.161***	0.106***	0.110***	0.015
		(0.026)	(0.021)	(0.021)	(0.035)
Sales of other yogurt		0.277***	0.251***	0.209***	0.353***
		(0.018)	(0.023)	(0.020)	(0.041)
Assortment Chobani		-0.096***	-0.060***	-0.050***	-0.117***
		(0.004)	(0.005)	(0.004)	(0.010)
Assortment regular yogurt		0.000	0.000	0.003***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Assortment other Greek yogurt		0.003*	-0.013***	-0.004**	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Store effects	Y	Y	Y	Y	Y
Week effects	Y	Y			
DMA-week effects			Y	Y	Y
Store time trend				Y	
R^2	0.92	0.92	0.94	0.95	0.95
Adjusted-R^2	0.91	0.92	0.93	0.94	0.94
Num.of observations	71,947	71,947	71,947	71,947	32,050

Huber-White robust SEs clustered at store level are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Columns (1)-(4) show the results from the full sample, and column (5) reports results from a subsample.

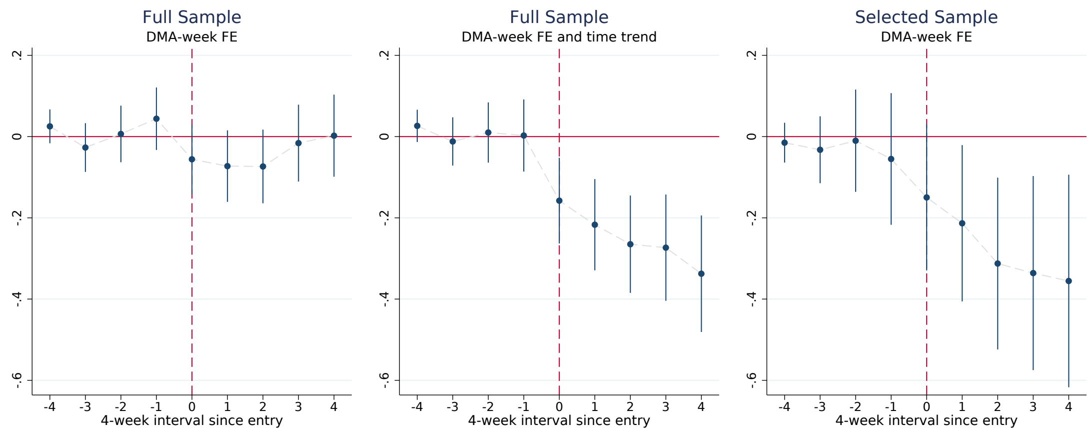
The change in *IncumbentPost* coefficient from column (1) to (4) exhibits a pattern similar to that for the Dannon entry regression. When including week fixed effects, column (2) shows a 12% increase in Chobani sales in the entered stores. Column (3) controls for DMA market specific week fixed effect. The *IncumbentPost* coefficient became negative, indicating a decrease of 7% in Chobani sales caused by the entry of Dannon and Yoplait. The negative impact from the entry of both incumbents doubles to a 15% reduction when store time trends are controlled for in column (4).

Column (5) in Table 3.3 reports results from a selected sample, which is almost half the size of the full sample. Chobani sales decline only by 10% in this subsample, a smaller drop than in the full sample stores. Also, store time trends are not included in column (5), because in the selected sample, entered stores and control stores have the same pre-entry trend even without accounting for store time trend in the parallel-trends test. One may notice this impact is smaller than the 30% decrease caused by Dannon's entry. Combining this finding and the reported positive effect from Yoplait's entry, when both Dannon and Yoplait entered, Chobani seems to have lost fewer sales than the situation in which Dannon was the only competitor. Such a statement should be made with caution as we cannot distinguish whether the difference is caused by the additional entry of Yoplait or heterogeneity between store samples.

To investigate the same issue that shared with the previous two entry events whether sales growth in control stores serves as a valid counterfactual of the entry stores, I also estimate the same model with entry leads and lags on the two incumbents' entry data. Figure 3.6 presents the coefficient plots of entry dummies with the 95% confidence interval.

The left plot in Figure 3.6 shows no evidence of anticipatory responses in the entered stores when controlling for DMA market specific week fixed effects. All four coefficients of

Figure 3.6. Dannon and Yoplait Effect: parallel trend test



This figure plots the estimated coefficients and the 95% confidence intervals for the entry leads and lags. Dannon and Yoplait Greek entered at week interval 0, marked by the red dashed line in each plot. The coefficients to the left of the red dashed line are the estimated anticipatory effects, and the coefficients to the right show the post-entry dynamics.

entry lead dummies are small and not statistically different from zero. However, a monotonic increasing trend occurs near the entry time. Controlling for store level growth rate in the second plot removes this trend. In this preferred specification, the coefficients of entry leads are extremely close to zero, providing stronger evidence that the pre-entry period parallel-trends assumption holds between entered stores and control stores. The post-entry effects exhibit some dynamics over time. The arrival of Dannon and Yoplait causes an immediate drop in Chobani sales, and the negative impact accumulates over time. This pattern is observed in the full sample controlling for store specific time trend.

Finding the same pattern can be shown in a sample without including store time trends would be more appealing. However, because many of the entered stores started to sell Chobani from the third or fourth quarter of 2009, matching used in the Yoplait entry case cannot be implemented in both incumbents' entry event. Since the subsample is constructed by excluding stores with very early or very recent Chobani entry, the difference in sales growth rate should be smaller than in the full sample. I thus apply the parallel-trends test in this sample without store specific time trend. Indeed, the coefficients of entry leads and lags are shown to be similar to the full sample with control of store time trends. Although the last entry lead coefficient shows a decreasing trend, the result confirms the finding from the full sample and the use of store time trends.

3.4. Conclusion

This chapter investigates the impact of Dannon and Yoplait's entry into the Greek yogurt segment on the store sales of Chobani. As a new yogurt manufacturer in the US market, Chobani was gaining shares, and expanding markets for Greek yogurt as well. The entry of big category incumbents can help the subcategory grow faster. The empirical ambiguity is whether Chobani was benefited or harmed by the subcategory entry of incumbents. The findings of this chapter show the entry impact differed depending on which incumbent entered. Yoplait's entry effect was positive. Chobani increased sales in Yoplait entry stores. On the contrary, Dannon's entry had a large negative impact on the store sales of Chobani.

A possible explanation for the difference in entry effect is that Dannon Greek is more competitive than Yoplait Greek. As mentioned earlier in Chapter 1, Yoplait Greek is considered "fake" Greek yogurt because it was made by adding milk concentrate, whereas Dannon insisted on producing Greek yogurt using the standard straining process. The low prices for Yoplait Greek yogurt can attract more consumers to the Greek segment, driving subcategory awareness. Since Yoplati Greek is not a "good" product, those consumers switch to Chobani as they become aware of Greek yogurt. Dannon Greek yogurt, on the hand, is of much better quality. It is such a strong competitor that can take sales from Chobani even when the total size of the Greek yogurt market is growing.

Another conclusion from this chapter is that entry was not random, especially the entry of Dannon. When the two incumbents entered, they likely used the store sales growth rate of Chobani to decide their entry strategies. If this is the case, simply applying the differences-in-differences model without considering the difference in growth rates among entered and non-entered store would lead to a biased estimate of the entry effect. In a test for pre-entry period time trends, the differences-in-differences model that does not control for market or store specific time trend failed to pass. The model with control for market and store specific growth rates is shown to have stronger credibilities in estimating a causal effect of entry.

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APPENDIX A

Construct Price Series in RMS Stores in Chapter 2

The Nielsen HMS sales data only provide information on products purchased by households. As a result, I cannot observe prices for other yogurt brands that were not purchased by the household, yet I require these unobserved prices for demand model estimation. To solve this problem, I fill in the unobserved prices using the RMS data. I first construct store-week-brand prices, and then match them with the HMS purchase data based on the store visited and the date purchased.

The RMS sales data are at the store-week-UPC level. In my study, UPCs are first grouped into seven brands: Dannon regular, Yoplait regular, private label, Fage, Chobani, Dannon Greek and Yopalit Greek. And all else are grouped together as "Others". For each brand, I run the following procedure to construct store-week prices:

(1) Calculate the weight of a UPC as its share of volume in the brand at a store in a given year.

(2) Normalize the UPC weights in each week to guarantee the sum of all UPCs weights for a brand is 1 in a given store-week.

(3) Construct the brand price as the share-weighted average of UPC prices in a given store-week.

The generated store-week-brand prices are then matched to HMS purchase data. Since I only consider shopping trips in the RMS stores, the match is simply based on the store or retailer identity and the week visited.

One problem with this simple match is that RMS data only contain information for UPCs with sales in the week. In other words, if a UPC has zero sales on shelves in the week, it will not appear in the data. Thus, this simple match may introduce some bias. However, because I group UPCs into brands and focus on large brands, I expect the bias, if any, will not significantly affect the results. In fact, for brands like Dannon and Yoplait regular yogurt, if carried in the store, missing prices in a given week occurs very rarely. For Greek yogurt brands, I do not impute missing store-week prices because of the unstable supply and varying entry timing. Instead, I remove the Greek yogurt brand from the choice set of a shopping trip during which its store-week price is not available.