ESSAYS ON PRICE DISCRIMINATION

by

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For my parents, Marvin and Davira

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table

CHAPTER I

Introduction

Walk into any retailer in the country and you will see the same thing; multiple versions of the same product, possibly produced by different manufacturers or with slightly different attributes, for sale at different prices. Economists refer to this phenomenon as price discrimination and have theoretically established that price discrimination generally harms consumers, raises profits and typically leads manufacturers and retailers to offer too much variety. Empirical studies have verified these results, but have also uncovered additional puzzles, such as why different retailers offer different versions of a product, or how competition distorts the price schedule of a versioned product.

This thesis explores the relationship between these two puzzles. In chapter II, I examine whether a monopolist offering different container sizes of a single product alters that product's price schedule when a new product is introduced. If a monopolist is willing to alter it's price schedule, then a common explanation for both puzzles exists; differing consumer tastes causes some firms to introduce new versions of a product while also distorting the price schedule of their existing product.

To assess the validity of this hypothesis, I modify a model of second-degree price discrimination so that consumers tastes for a product differ across two dimensions; a vertical dimension representing a consumer's taste for convenience and a horizontal dimension representing a consumer's taste for a particular product. This model yields a surprising result; if consumer tastes are separable over these two dimensions, then the introduction of a new product does not distort the price schedule of an existing product. In other words, the model suggests that the only way that a new product introduction could explain both puzzles is for consumers who prefer convenience to also prefer a particular product

Using detailed, store-level data from the Dominick's Fine Foods supermarket chain, I test the model's prediction by investigating whether stores within this chain distort the prices of different sizes of a sport drink when they introduce a new sports drink. Sports drinks are an ideal choice for studying this trade-off; unlike other products sold in Dominick's stores, sports drinks are almost completely characterized by their size, manufacturer, and flavor, all of which are observed in the data. Moreover, since the number of sports drinks sold by Dominick's stores increases over the course of the sample, the data contain a number of opportunities to examine the effect of product entry and exit.

I find that a product release distorts the relative prices of a product's adjacent container sizes. This result suggests that consumer tastes are not independent, which supports the hypothesis that new product introduction can explain both puzzles.

Chapter III (joint with Ron Borzekowski and Raphael Thomadsen) continues this investigation by relaxing the single-firm assumption, thereby allowing competing firms to sell multiple versions of different products. In particular, we examine how the presence of additional competitors affects the number of product variants offered by a firm. The mail order catalog industry proves to be a useful setting in which to assess the relationship between price discrimination and competition. Because mailing lists are pure information goods, they have zero marginal costs. Hence, any price variation cannot be attributed to cost differences and must therefore be attributed to price discrimination.

Another advantage of zero marginal costs is that we may focus on the firm's decision whether to price discriminate (by offering selects), and if so, the firm's choice of the number of options presented to consumers. Examining the decision to price discriminate provides a direct way to measure whether the prevalence of price discrimination is higher or lower in competitive markets.

The results indicate that increased competition is generally associated with an increased propensity to price discriminate. Further, list owners offer menus with more choices in more competitive markets. That is, not only are lists in more competitive segments more likely to price discriminate, they will also partition their consumers into finer subsets.

These results, like those from chapter II, suggest that the relationship between price discrimination and the presence of close substitutes is largely dictated by consumer preference. This is sensible given that the major difference between the monopolist and competitive regimes is control; the supermarkets in chapter II are able to choose which horizontally differentiated products to stock as well as how to price these products, while the list owners in chapter III must set their prices *conditional* on their competitors' product offerings and price schedules. This distinction implies that only the magnitudes of the effects should differ.

CHAPTER II

To Discriminate or Differentiate? Evidence From a Supermarket Chain

2.1 Introduction

Retailers with market power can extract consumer surplus by introducing new products (horizontal differentiation) or by offering existing products in different sizes (price discrimination). Both strategies have their advantages; spatial Hotelling models suggest that a retailer can increase its profits by adding new horizontally differentiated products and then raising the price on all of its products. Models of second-degree price discrimination also suggest that retailers can raise profits by offering a menu of price\size alternatives and allowing customers to select the alternative that most suits them.

While both horizontal differentiation and price discrimination are individually profitable strategies, little work has been done to determine how these strategies interact. I extend a model of second-degree price discrimination to show that when consumer tastes for horizontal differentiation and price discrimination are independent, the introduction of a horizontally differentiated product causes the prices and profits on an existing related product to fall, but does not distort the relative price of adjacent menu alternatives. These results suggest that retailers need not sacrifice their ability to price discriminate on an existing product when they introduce a new product.

Using detailed, store-level data from the Dominick's Fine Foods supermarket chain, I then investigate whether stores within this chain trade the return from offering an existing sports drink in different container sizes (price discrimination) for the return from introducing new products (horizontal differentiation). Sports drinks are an ideal choice for studying this trade-off; unlike other products sold in Dominick's stores, sports drinks are almost completely characterized by their size, manufacturer, and flavor, all of which are observed in the data. Moreover, since the number of sports drinks sold by Dominick's stores increases over the course of the sample, the data contain a number of opportunities to examine the effect of product entry and exit.

My investigation into the relationship between differentiation and discrimination is complicated by the fact that stores choose which sports drinks to stock as well as how to price these products. These choices are contingent on a number of store-specific factors not observed in the data, including competition between neighboring grocers, the vertical relationship between stores and sports drink distributors, and whether a store chooses to prominently display a sports drink product.

I use the delay in a store's receipt (removal) of a product as part of a differences-in-differences strategy to distinguish the effect of new product entry from the effects of these unobserved factors. Provided that the order in which stores receive (remove) products is uncorrelated with unobserved factors affecting a store's pricing policy, differences-in-differences allows me to identify the causal effect of product entry (exit) on an existing product's price schedule.

The above strategy assumes that conditional on observables, all existing products will be affected by another product's entry or exit in a similar fashion. Theory suggests, however, that the degree to which products substitute for one another plays an important role in this process. Products that are not close substitutes for a new product should experience little distortion in their price schedules and menu offerings when a new product enters, while products that are close substitutes should experience substantial distortions. As a result, the differences-in-differences strategy should understate the causal effect of product entry. I remedy this by first using Bayesian methods to estimate consumer preferences for sport drink SKUs, and then employ these estimates to capture a product's sensitivity to another product's introduction (removal).

I find that a product release hampers the monopolist's ability to price discriminate by distorting the relative prices of a product's adjacent container sizes. In particular, a product release typically causes the price gap to drop by 6%. A product retirement, however, has no effect on the price gap.

Few empirical researchers have examined how multi-product retailers with market power exchange price-discrimination for horizontal differentiation. Draganska and Jain (2006) use a structural model to analyze whether consumers value horizontally differentiated yogurt flavors more than vertically differentiated yogurt product lines. Having established that consumers value line attributes more than flavor attributes, Draganska and Jain go on to determine whether manufacturers use product lines to price discriminate. While this analysis represents the first step in examining how yogurt manufacturers might trade flavors for products, Draganska and Jain do not explicitly examine this exchange.

A number of empirical studies have also examined a related problem, the relationship between competition and price discrimination. Busse and Rysman (2005) find that competition increases the curvature in the price schedule of yellow pages advertisements, while Seim and Viard (2004) find that increased competition leads to a proliferation of wireless calling plans. Likewise, Borzekowski et al. (2006) find that increased competition amongst direct mailers is associated with an increased propensity to price discriminate.

The main difference between these studies and the one that I propose is that Dominick's supermarkets are able to choose which horizontally differentiated products to stock as well as how to price these products, while firms in these studies choose their prices *conditional* on their competitors' product offerings and price schedules. This distinction implies that Dominick's supermarkets can better manage the trade-off between differentiation and discrimination than firms facing competition.

2.2 A Model of Price Discrimination

I use a variant of the second-degree price discrimination problem proposed by Itoh (1983) to explore the relationship between horizontal differentiation and price discrimination. Itoh's model describes a single-product monopolist who engages in nonlinear pricing by offering it's product in a number of quality levels at different prices to consumers with heterogeneous tastes for the monopolist's product. Itoh's model distinguishes itself from the canonical model of second degree price discrimination in that the monopolist is restricted to offering its customers a fixed number of quality levels[1] Nevertheless, Itoh's model yields similar conclusions as Mussa and Rosen (1978); even if a monopolist only knows the distribution of consumer tastes, it can induce consumers to reveal their tastes by appropriately choosing the prices of its different quality levels. Limits on the number of quality levels allows Itoh to

[1] Although not explicitly incorporated into the model, Itoh points out that this restriction could be due to fixed costs, like shelving constraints.

explore how the addition or subtraction of quality levels affects the price schedule.

While Itoh's model explicitly deals with only one product, in fact two products are present; the good produced by the monopolist and the "outside good" whose value must be accounted for by the monopolist to ensure that consumers are willing to purchase the monopolist's product. The outside good plays the part of the next best alternative to the monopolist's product, and can be thought of as the value of a horizontally differentiated product.

Unfortunately, Itoh assumes that all customer's value the outside option identically, making it impossible to examine the relationship between differentiation and discrimination. Below, I present a modified version of Itoh's model with this assumption relaxed. Rather than assuming that consumers only vary vertically in their tastes for quality, I assume that consumers also vary horizontally in their taste for the monopolist's product. By relaxing this assumption, I can examine how a monopolist's pricing strategy is affected by the decision to introduce new quality levels as well as new products.

This model can be readily seen as a version of Rochet and Stole (2002), where the number and quality of the menu options offered by the monopolist is discrete and the monopolist sells multiple products. One other difference between this model and Rochet and Stole's is that the monopolist is prohibited from choosing a product's quality levels. Instead, the monopolist is allowed to choose the price of the different menu alternatives as well as which alternatives it sells.

2.2.1 Consumers

Consider a monopolist who initially offers its customers a single product in M quality levels. Denote the sequence of price\quality pairs for product the monopolist's product as $A = \{(p_m, q_m)\}_{m=1}^{M}$, with $q_M < q_{M-1} < \ldots < q_1$. Each customer faces the option of either purchasing one of the M versions in A or not purchasing the product. The utility of the ith consumer is described by

$$U_{im} = \begin{cases} \theta q_m - p_m & \text{if } i \text{ purchases } m \in A \text{ ;} \\ \tau x & \text{otherwise.} \end{cases} \tag{1}$$

Equation 1 indicates that Consumer i's utility is completely characterized by the random variables (θ, x), with $\theta \in [\underline{\theta}, \bar{\theta}]$ and $x \in [0, \bar{x}], \bar{x} \leq 1$. While $\frac{\partial U}{\partial q} > 0$ implies that all consumers value higher quality, consumers with a higher θ value quality more than those with a lower θ. Likewise, consumers with a lower x value product j relatively more than those with a high value. x corresponds to a linear city model with consumers distributed along the $[0, \bar{x}]$ line segment and the monopolist's product located at 0. τ is often interpreted as the "transportation cost" that a consumer must accrue to purchase the monopolist's product. Throughout, I assume that θ and x are independently and uniformly distributed, with cumulative distribution functions $F(\theta) = \frac{\theta}{\bar{\theta} - \underline{\theta}}$ and $G(x) = \frac{x}{\bar{x}}$, and densities $f(\theta) = \frac{1}{\bar{\theta} - \underline{\theta}}$ and $g(x) = \frac{1}{\bar{x}}$.

For a given value of x, a consumer will choose (q_m, p_m) if and only if

$$\theta q_m - p_m \geq \tau x, \quad \forall m \leq M$$

$$\theta q_m - p_m \geq \theta q_n - p_n, \quad n \neq m$$

The first inequality, known as the individual rationality constraint, ensures that the consumer is willing to purchase at least one of the alternatives offered by the monopolist. The second inequality, known as the incentive compatibility constraint, ensures that the consumer never wishes to choose any other alternative but the one designed for him. Because consumer preferences satisfy the single crossing property

($U_{q\theta} > 0$) and utility is increasing in type ($U_\theta > 0$), the above constraints become

$$\theta q_M - p_M \geq \tau x$$
$$\theta q_m - p_m \geq \theta q_{m+1} - p_{m+1}, \quad \forall m < M$$

In other words, the monopolist needs only choose menu prices so as to prevent consumers from purchasing the next lowest quality level.

It is important to note that x only appears in the individual rationality constraint. This occurs because there is no interaction between θ and x in equation 1. The absence of any interaction mirrors the independence assumption made earlier; people who enjoy the monopolist's product more intensely do not also value higher quality versions of that product more intensely. This assumption implies that the presence of close substitutes will not affect the price markup of the add-ons.

To derive the demand for the mth quality level, let θ_m denote the customer type that is indifferent between purchasing the mth and $m+1$st quality levels. Then the above inequalities imply that the market demand for the mth quality level is given by

$$\int_{\theta_m}^{\theta_{m-1}} f(\theta) d\theta.$$

where $\theta_m = \frac{\Delta p_m}{\Delta q_m}$, $\Delta p_m = p_m - p_{m+1}$ and $\Delta q_m = q_m - q_{m+1}, \forall m < M$; $\theta_0 = \bar{\theta}$ and $\theta_M = \frac{p_M + \tau x}{q_M}$.

2.2.2 The Single-Product Monopolist

Conditional on x, the monopolist earns profits (excluding fixed costs)

$$\begin{aligned}
\pi(\mathbf{p}, x) &= \sum_{m=1}^{M} \int_{\theta_m}^{\theta_{m-1}} (p_m - C_m) f(\theta) d\theta \\
&= (p_M - C_M) \int_{\theta_{M(x)}}^{\bar{\theta}} f(\theta) d\theta + \sum_{m=1}^{M-1} (\Delta p_m - \Delta C_m) \int_{\theta_m}^{\bar{\theta}} f(\theta) d\theta \\
&= \frac{1}{\bar{\theta} - \underline{\theta}} \left[(p_M - C_M)(\bar{\theta} - \theta_{M(x)}) + \sum_{m=1}^{M-1} (\Delta p_m - \Delta C_m)(\bar{\theta} - \theta_m) \right]
\end{aligned}$$

where C_m is the cost associated with producing quality level q_m, $\Delta C_m = C_m - C_{m+1}$ and $\mathbf{p} = (p_M, \{\Delta p_m\}_{m=1}^{M-1})$. The second line suggests an alternate way to view price discrimination. Rather than offering its consumers a sequence of alternatives from which to choose, the monopolist can equivalently offer a low quality base product along with a sequence of higher quality "add-ons". The low quality base product is purchased by all the monopolist's customers, while each higher quality add-on is only purchased by customers with progressively higher θs.

Because the quality levels are chosen by the manufacturer, the monopolist only needs to choose the sequence of prices $\mathbf{p}$ to maximize profits. In other words, the monopolist solves

$$\begin{aligned}
&\max_{\mathbf{p}} \quad E_x[\pi(\mathbf{p}, x) | x \leq \tilde{x}] && \Leftrightarrow \\
&\max_{\mathbf{p}} \quad (p_M - C_M) \int_0^{\tilde{x}} \int_{\theta_{M(x)}}^{\bar{\theta}} f(\theta) d\theta g(x) dx + \\
&\qquad\quad G(\tilde{x}) \sum_{m=1}^{M-1} (\Delta p_m - \Delta C_m) \int_{\theta_m}^{\bar{\theta}} f(\theta) d\theta && \Leftrightarrow \\
&\max_{\mathbf{p}} \quad (p_M - C_M) \frac{\tilde{x}}{\bar{x}(\bar{\theta} - \underline{\theta})} \left[\bar{\theta} - \frac{2p_M + \tau\tilde{x}}{2q_M} \right] + \\
&\qquad\quad \frac{\tilde{x}}{\bar{x}(\bar{\theta} - \underline{\theta})} \sum_{m=1}^{M-1} (\Delta p_m - \Delta C_m)(\bar{\theta} - \theta_m)
\end{aligned}$$

where

$$\tilde{x} = \min \left\{ \frac{\bar{\theta} q_M - p_M}{\tau}, \bar{x} \right\}. \tag{2}$$

$\tilde{x}$ represents the final horizontal type willing to purchase some version of the monopolist's product. Equation 2 indicates that the monopolist may find it optimal to serve only a subset of the horizontal market. Moreover, equation 2 suggests that when the entire horizontal market is not served, the marginal type will be determined by the price of the lowest quality alternative.

Differentiating with respect to $\mathbf{p}$ yields

$$\begin{aligned}
&\tilde{x} \left[\bar{\theta} - \frac{2p_M + \tau \tilde{x}}{2q_M} \right] - \frac{p_M - C_M}{q_M} \tilde{x} + \\
&\frac{\partial \tilde{x}}{\partial p_M} \left[(p_M - C_M) \left(\bar{\theta} - \frac{p_M + \tau \tilde{x}}{q_M} \right) + \sum_{m=1}^{M-1} (\Delta p_m - \Delta C_m)(\bar{\theta} - \theta_m) \right] = 0 \qquad (3) \\
&\Delta p_m = \frac{\bar{\theta} \Delta q_m + \Delta C_m}{2}, \quad \forall m < M \qquad (4)
\end{aligned}$$

where

$$\frac{\partial \tilde{x}}{\partial p_M} = \begin{cases} -\frac{1}{\tau} & \text{if } \tilde{x} = \frac{\bar{\theta} q_M - p_M}{\tau}; \\ 0 & \text{if } \tilde{x} = \bar{x}. \end{cases}$$

These conditions identify a maximum since the profit function is quasi-concave in $\mathbf{p}$.

Equation 3 indicates that when the entire horizontal market is served, $\frac{\partial \tilde{x}}{\partial p_M} = 0$ and the price of the lowest quality alternative (p_M) is independent of the prices of higher quality alternatives. However, if only a subset of the horizontal market is served, equation 3 implies that any changes in the price gap between adjacent higher quality alternatives will also alter the price of the lowest quality alternative.

One important feature of equation 4 is that Δp_m is not a function of either p_M or $\bar{x}$. Their absence implies that the price gap between adjacent menu items is independent of the extent of the horizontal market served ($\tilde{x}$) and yields the following result

Proposition 1. *Serving fewer (more) horizontal types increases (decreases) the price of all menu items by the same amount*

Proof. Suppose that the horizontal market is covered so that $\tilde{x} = \bar{x}$. Then $\frac{\partial \tilde{x}}{\partial p_M} = 0$ and equation 3 may be rearranged so that $p_M = \frac{\bar{\theta} q_M - \tau\tilde{x} + C_M}{2}$. Totally differentiating the first order conditions around $\mathbf{p}^*$ yields

$$\begin{aligned}\frac{dp_M}{d\tilde{x}} &= -\frac{\tau}{2} < 0 \\ \frac{d\Delta p_m}{d\tilde{x}} &= 0, \quad \forall m < M\end{aligned}$$

By definition, $p_m = p_M + \sum_{i=m}^{M-1} \Delta p_i$, $\forall m < M$, which in turn implies $\frac{dp_m}{d\tilde{x}} = \frac{dp_M}{d\tilde{x}} + \sum_{i=m}^{M-1} \frac{d\Delta p_i}{d\tilde{x}}$. Hence, $\frac{dp_m}{d\tilde{x}} = \frac{dp_M}{d\tilde{x}} < 0 \; \forall m$. □

Proposition 1 indicates that any changes in the extent of the horizontal market served will only affect the price of the lowest quality alternative. Intuitively, the monopolist can only serve more of the horizontal market (x) by setting a low price on the base version of its product and serving lower quality customers in the vertical market (θ). As the size of the horizontal market shrinks, it becomes easier for the monopolist to capture more of the horizontal market, allowing it to raise the price of its base product and serve higher quality customers in the vertical market.

2.2.3 A New Product Arrives

Now, suppose that the monopolist introduces a second product at $\bar{x}$ and offers M_2 versions of this product. Let x_1 and $1 - x_2$ denote the location of the last horizontal consumer served by each product. If no version of this new product is a close substitute for any version of the existing product, then $x_1 < x_2$; there exists some horizontal consumer type who is unwilling to purchase either of the monopolist's products. In this instance, the marginal consumer types x_1, x_2 will not be a function of the other product's price schedule, and the results from section 2.2.2 may be applied to each product individually.

If, however, the new product is a close substitute for the existing product, then $x_1 = x_2 = \tilde{x}$, and the market for each product will be determined by the prices of both products' lowest quality version. Nevertheless, the independence between horizontal and vertical tastes still implies that the price gap between adjacent quality levels of the first product will be unaffected by the introduction of the second product. These ideas are formalized in the following propositions (proved in Appendix II.A):

Proposition 2. *If a product has the same number and quality of add-ons as a second product, then introducing (removing) that product does not affect the prices of the second product's add-ons.*

Proposition 3. *Adding products cannibalizes profits from existing products.*

Propositions 2 and 3 concretely demonstrate the relationship between horizontal differentiation and price discrimination. If shelving space is not scarce and markets not local, Propositions 2 and 3 show that the introduction of new products causes a parallel shift in an existing product's demand curve, decreasing profits from that product but leaving that product's price schedule undistorted.

2.2.4 Discussion

The purpose of this model is to explore whether a monopolist, when choosing to sell different brands and sizes of a product, will sacrifice some if its ability to price discriminate in favor of new products. The above results suggest that when the monopolist is free to offer as many different products and sizes as it wishes, then there is no trade-off between price discrimination and horizontal differentiation.

The absence of any distortion in a product's price schedule is a direct consequence of two assumptions 1) the utility function is additively separable in θ and x, and 2) θ and x are independently of one another. Together, these assumptions imply that consumers who enjoy product 1 more than product 2 do not necessarily enjoy a smaller container of product 1. This is a reasonable assumption to make when examining products like sports drinks, and one that I will test in section 2.6.

2.3 Data

I test the above predictions using data on stores in the Dominick's supermarket chain obtained from the University of Chicago's Kilts' Marketing Center to test some of the above predictions. Kilts maintains a database containing weekly sales, retail price, wholesale price, and display information for many of the SKUs sold at each of the 93 supermarkets in the Dominick's Fine Foods chain over a 7 year period beginning in 1989. SKU stands for Stock Keeping Unit, or the level at which a unit of sale is identified in the data. Here, an SKU is identified by its manufacturer, flavor and size. Also, a product is defined as the collection of SKUs with the same manufacturer and flavor.

The Kilt's data also houses a database of store-level characteristics, including data from the Census blocks surrounding each store, as well as information about each stores' weekly revenue and attendance.

2.3.1 Sports Drinks

These data cover an important period in the sports drink market. Over the course of the sample, Gatorade's twenty-year monopoly faced two major challenges, first by Coca-Cola's Powerade product line in 1992, followed a year later by Pepsi's All-Sport line. Table 2.1 displays the total sales and U.S market shares of each firm from 1988-1997. This table demonstrates that the sports drink market underwent a major expansion over the course of the sample; total sales doubled from 1988-1994. Moreover, despite its best efforts, Gatorade was unable to prevent either All-Sport or Powerade from eroding its position; Gatorade's market share fell from 82.4%, the year that All-Sport first entered to 73.1% by 1997.

Figure 2.1 demonstrates that competition amongst these manufacturers unfolded somewhat differently across Dominick's stores. Unlike the national market, where Powerade was the first to compete against Gatorade, All-Sport was the first to compete against Gatorade in Dominick's stores, entering the market in the 183rd week of the sample. Powerade's entry was postponed until the 242nd week, more than a year after All-Sport's entry. Apparently, entering earlier was advantageous to All-Sport; unlike the national market where their share lagged Powerade's, All-Sport market share dominated Powerade's for most of the sample. Figure 2.1 also indicates that Dominick's stores differ from the national market in one important way; although Gatorade is clearly affected by both All-Sport and Gatorade's presence, the figure indicates that by the end of the sample, Gatorade had regained virtually the entire market.

Table 2.2 lists the 68 sport drink SKUs that are present over the course of the sample[2] by manufacturer, flavor, size, and its first and last appearance in the sample.

[2] I omit 6 SKUs from the sample; 5 of these SKUs have no identifiable flavor information and the 6th is omitted because it is the sole SKU sold in powder form.

Notice how Gatorade's products dominate the data; Gatorade's has 46 SKUs in the sample, almost 3 times All-Sport's and 4 times Powerade's. Gatorade also has more flavors than either Gatorade or All-Sport (14, compared to 6 and 7) as well as more sizes per flavor (a median of 4 compared to 3.5 and 2). Gatorade is also responsible for virtually all of the new flavors present in Dominick's stores; 6 of the 9 new flavors that entered Dominick's were produced by Gatorade (All-Sport had one new flavor, Powerade had two new flavors).

2.3.2 How Products Are Priced, Introduced, and Removed

Dominick's corporate office typically chooses which products its stores carry and which prices they charge. Chintagunta, Dub, and Singh (2003) describe how Dominick's uses zone pricing as a form of third-degree price discrimination. According to Chintagunta et al., Dominick's pricing zone policy evolved over time, growing from 3 zones in 1990 to 16 pricing zones by 1992. These authors also describe how stores within a zone rarely sell a product for the same price, as well as how prices are less dispersed within a zone than across zones.

Chintagunta et al.'s finding that that Dominick's engages in a form of third degree price discrimination suggests that Dominick's stores possess some degree of market power. The chain's ability to price discriminate is supported by Hoch, Kim, Montgomery, and Rossi (1995), who find that that while store-level category [3] price elasticities are sensitive to the proximity of competitors, competitive effects are relatively unimportant when compared to measures of store market power.

In addition to setting prices, Dominick's corporate office also decides which products individual stores will carry. The corporate office maintains a team of corporate buyers who maintain a particular product category. When a new product is released,

[3] categories are collections of products. Examples include cookies, juice, sodas, soups, and cigarettes. Sports drinks are listed in both the bottled juice and carbonated sodas categories.

"roll-out" teams go from store to store to install a new product in its category. These buyers also determine when to remove a product from their shelves.

Store managers also play a role in this process. They pass on consumer requests for a particular product to the corporate office, and if corporate decides to no longer carry a particular product, can negotiate directly with a product's manufacturer to obtain a product.[4]

The roll-out process generates a good deal of turnover. Over the course of the sample, I observe 8,421 distinct SKU additions and subtractions across all Dominick's stores. Entry and exit is split roughly equally across stores with 4,066 new SKUs introduced and 4,355 existing SKUs removed. Every SKU either enters or exits at least one store over the course the sample.

Figure 2.7 succinctly displays how sports drink inventories differ across stores within the Dominick's chain. I construct figure 2.3a by first calculating the fraction of all SKUs that each store sells in a particular week, and then plotting that fraction for stores at the 75th (dashed), 50th (solid), and 25th (dashed) percentiles. The leftmost horizontal line marks All-Sport's entry into the chain, while the rightmost line marks Powerade's entry. Figure 2.3b is similar to figure 2.3a except that it displays the fraction of all *products* sold by each store during a given week.

Taken together, these graphs suggest that prior to All-Sport's introduction, each store carried all of Gatorade's flavors but that virtually no store stocked all the sizes that each product was offered in. The increase in store shares that occurs before All-Sport's entry could either be a result of each store carrying more sizes or Dominick's corporate discontinuing some of the sizes. Table 2.2 indicates that during this period, Dominick's stopped selling four SKUs but began selling 6 new SKUs, which suggests

[4] I obtained this institutional detail from an interview with a Dominick's store manager.

that stores began carrying more sizes.

After All-Sport's release, these graphs show that stores began carrying a smaller fraction of all SKUs as well as a smaller fraction of all products. An explanation again comes from table 2.2, which reveals that all of All-Sport's and Powerade's flavors at entry duplicated Gatorade's flavors, and that virtually all of Gatorade's products are sold throughout the sample. These observations suggest that stores chose to conserve scarce shelf-space by not offering duplicate flavors.

2.3.3 Do Supermarkets Price Discriminate?

Having established that stores in the Dominick's chain horizontally differentiate by offering sports drink in different brands and flavors, I must now determine whether or not stores price discriminate by offering the same product in multiple container sizes. Specifically, I test whether stores use container sizes the same way as the monopolist in section 2.2 uses quality levels; to screen consumers. If consumers value conveniently sized packaging, then the smallest container size may be interpreted as the highest quality good and the largest container size the lowest quality good. This interpretation is consistent with the observation that smaller containers of sports drinks typically have a higher price per unit ounce than larger container sizes.

Equation 24 predicts that a price-discriminating monopolist's price schedule will be a nonlinear function of container size. To test this prediction, I regress

$$\begin{aligned} \log\left(ppo_{mjst}\right) = \beta_0 + \beta_1 \log\left(cpo_{mjst}\right) + \beta_2 bundle_m \\ + \delta_v + \alpha_s + \gamma_j + \phi_b + \omega_t + \epsilon_{mjst} \end{aligned} \tag{5}$$

where ppo_{mjst} and cpo_{mjst} are retail and wholesale price per unit ounce, γ_j is the coefficient on the product j dummy to which SKU m belongs, and $\phi_b, \alpha_s, \omega_t$ are the coefficients on brand, store, and week dummies. δ_v are the coefficients on a series of volume dummies that measure the percentage change in price due to the number of fluid ounces in SKU m, relative to the 128 ounce size. $bundle_m$ is an indicator variable equal to 1 if an SKU is a bundle of other SKUs and is included to distinguish the 16 ounce 4-pack from the 64 ounce container size.

Equation 5 uses price variation across stores, weeks, and products to estimate δ_v. Normally, δ_v would not identify price discrimination because price variation could be due to differences in the marginal cost of producing larger sizes, requiring me to implement a strategy similar to Shepard (1991) or Cohen (2004) in order to identify price discrimination. Fortunately, the data include a measure of SKU wholesale prices, making these strategies unnecessary.

Figure 2.3 displays the OLS estimates of δ_v. The dashed line plots the price schedule on the typical sports drink before the 16 ounce container size was replaced with the 20 ounce size, while the solid line depicts the price schedule after the replacement[5]. Both price schedules confirm the theoretical prediction; retail prices are indeed nonlinear in container size. Whatsmore, the decline in price per ounce depicted in both schedules supports an important theoretical prediction made by Maskin and Riley; quantity discounting.

2.4 Estimation Strategies

Having established that stores both differentiate and discriminate, I use a variant of differences-in-differences (DIFF) to examine how the introduction or removal of a horizontally differentiated product affects the prices of an existing product's menu items. I use Proposition 2 as my null hypothesis; under the assumption that horizontal and vertical tastes are separable and shelving space not scarce, introducing

[5] All size dummies are statistically significant at the 99% level.

(removing) a horizontally differentiated product does not distort the relative prices of adjacent container sizes. I test this proposition using the difference in price between adjacent container sizes before and after a product is released (removed).

Unfortunately, the DIFF strategy assumes that conditional on an SKU's observables, the addition or subtraction of a product always affects existing SKUs in the same way. For example, suppose that a store selling only the lemon-lime flavor introduces the tropical fruit flavor in week 82 and the grape flavor in week 126. The DIFF strategy assumes that on average, the introduction of the grape flavor will have a similar effect on the lemon-lime and tropical fruit flavors as the introduction of the tropical fruit flavor had on the lemon-lime flavor.

To see why this might prove false, suppose that consumers prefer to not purchase any sports drink to purchasing the tropical fruit flavor but always prefer grape to both lemon-lime and tropical fruit. Then the introduction of the tropical fruit flavor does not change the value of the outside option and should therefore not affect the price schedule of lemon-lime SKUs. On the other hand, since consumers always prefer grape to both lemon-lime and tropical fruit, the introduction of the grape flavor should increase the value of the outside option, changing the price schedule for both lemon-lime and tropical fruit SKUs. In this instance, the DIFF strategy mistakenly averages the outcome of the two new flavor introductions together, understating the effect of a close substitute.

I remedy this problem by structurally estimating an SKU's demand curve and conditioning the DIFF strategy on the probability that an entering (retiring) product affects that SKU. Doing this allows each SKU to respond differently to a product entry or exit, enabling the DIFF strategy to distinguish products that affect the value of the outside option from products that do not.

The estimation strategy described above will only capture the trade-off between discrimination and differentiation if the following assumptions hold. First, I assume that stores are embedded in distinct markets. This assumption implies that consumers find it too costly to travel from one supermarket to another searching for deals on sports drinks. If this assumption fails, then competition amongst subsets of stores, and not the introduction of new products could affect the tests described above. For similar reasons, I assume that competition between Dominick's and other supermarket chains (like Jewel-Osco) occurs at the chain rather than at the store level. Later, I will provide evidence supporting these assertions.

2.5 Estimating Differences in Differences

The main objective of my DIFF analysis is to estimate the causal effect of a product's introduction (removal) on a supermarket's ability to price discriminate over one of its existing (remaining) products, *conditional on that supermarket eventually adopting the new product*. Conditioning on adoption ensures that my estimates will remain unbiased even if my empirical specification does not properly account for why some supermarkets choose to never adopt (remove) a product.

Why use DIFF? A simple comparison of retail price markups before and after a product release (removal) should indicate how firms trade off discrimination and differentiation. Unfortunately, this comparison will only capture the effect of interest if no other factors are driving the store's decision to introduce (retire) the product. If, say, stores add (remove) products because demand for sports drinks increases (decreases) then the resulting change in the outcome of interest will capture both the change due to the demand increase (decrease) as well as the effect on price discrimination.

DIFF solves this problem by identifying a control group; in this case, stores that experience the demand increase but are delayed in receiving the new flavor. For this group of stores, the change in the outcome is due entirely to the change in demand. DIFF is constructed by subtracting the change in the outcome due exclusively to the change in demand from the simple difference described above, thereby isolating the effect of price discrimination.

Table 2.3 demonstrates how store adoption times vary. There, I identify the first week that a new product appears in one of Dominick's stores and then examine the fraction of eventual adopters who adopt that product for 10 weeks after the product's first appearance. This table reveals that virtually every store that eventually adopts a product does so by the 10th week following the product's introduction, with 3/4 of all stores adopting a product after the 3rd week.

Table 2.3 also shows that much of the variation in store adoption times is manufacturer-related. Many of Powerade's and Gatorade's products are almost universally adopted after the 3rd week, while All-Sport's products take until the 8th week to achieve similar penetration. Powerade's Mountain Blast and Tidal Burst flavors are the exception to this pattern; both enter stores at markedly slower rates than other Powerade products.

Exiting products exhibit similar variation. Table 2.4 displays the fraction of retirees who discontinue a product 10 weeks before the final retiree discontinues the product. The fraction of retirees still selling the product remains relatively constant until 4 weeks before the final store retires, when it decreases exponentially. This suggests that like new products, Dominick's chain sets target dates for the removal products from certain stores.

The main difference between the entry and exit is that some stores apparently choose to discontinue products well before the Dominick's chain requires them to. For instance, table 2.4 indicates that 10 weeks before the final retirement, roughly half of all retirees had already stopped carrying some of All-Sport's products. For these retirees, it seems likely that store-specific events and not chain policy lead retirees to stop selling the product. If these events are correlated with a store's pricing strategy then my estimation strategy will not identify the causal effect of entry (exit).

2.5.1 Specification

I implement a version of DIFF using the following specification

$$\begin{aligned}\Delta ppo_{mst} &= \beta_0 + \beta_1 \Delta cpo_{mst} + \beta_2 bundle_m + \delta_v \\ &\quad + \sum_{l=-4}^{4} \delta_l treat_{lst} + \epsilon_{mst} \end{aligned} \tag{6}$$

where

$$\begin{aligned}\Delta ppo_{mst} &= \frac{price_{mst}}{ounces_m} - \frac{price_{(m+1)st}}{ounces_{m+1}}, \\ \Delta cpo_{mst} &= \frac{\text{wholesale price}_{mst}}{ounces_m} - \frac{\text{wholesale price}_{(m+1)st}}{ounces_{m+1}}.\end{aligned}$$

Following **?**, I capture the causal effect of product entry and exit by defining the following dummies

$$treat_{lst} = \begin{cases} D_s 1(t \leq \tau_r - 4) \\ D_s 1(t = \tau_r + l), \quad \text{for } -4 < l < 4 \\ D_s 1(t \geq \tau_r + 4) \end{cases}$$

where D_s is an indicator for whether a product has entered (exited) a store, τ_r is the week that a product r enters (exits) a store, and $1(A)$ equals 1 if A is true and 0 otherwise.

These dummies play an integral role in my analysis. To see how, recall that SKUs enter and leave the Dominick's chain throughout the sample, making these different events difficult to compare. The relative time dummies $\delta = (\delta_{-4}, \ldots, \delta_4)$ ease this comparison by normalizing entry (exit) to a common week 0.

Furthermore, absent any other factors that influence price, δ represents the trend in the price gap between adjacent container sizes in the month surrounding a product release (retirement). In particular, equation 6 represents a direct test of Proposition 2. This proposition predicts that $\delta_0 - \delta_{-1} = 0$; Δppo_{mst}, which captures the difference in the price per ounce of adjacent container sizes, will not change when products are introduced (removed). The remaining elements of δ serve as diagnostic tool; they highlight retail price trends that are not captured by other regression covariates.

Weekly demand shocks, including holidays, sporting events, and weather could obscure the effect of product entry (exit). I control for these phenomena by first differencing each SKU from the next largest size sold each week. First differencing also controls for store, size, product, and manufacturer fixed effects.

2.5.2 Results

To test Proposition 2, I identify the week in which a product first (last) enters (exits) the Dominick's chain and then execute regression 6 on stores that adopt (retire) the product within 8 weeks of that initial (terminal) date. Doing so excludes stores who are either late adopters (retirees) or never adopt (retire) the product.

The theoretical model developed in section 2.2implicitly assumed that supermarkets could stock as many different SKUs as they wished. As figure 2.7 demonstrates, most supermarkets have limited shelf space that prevents them from offering all available sport drink SKUs. If shelving space is limited, then in order to introduce a new product, supermarkets may have to remove an existing SKU. Hence, the SKU removal and not the new product introduction may be driving price changes.

Although the data do not contain information on the amount of shelving space dedicated to sports drinks, I account for its presence by only including events where products are introduced (removed), but no SKUs are removed (introduced).

I plot estimates of the relative time dummies (δ) against weeks to release (retirement) in figure 2.4. The solid blue line plots the regression coefficients, while the dashed brown lines surrounding the blue display the 95% confidence interval. The gap at week -1 is meant to ease interpretation of the graphs; omitting δ_{-1} implies that the remaining time dummies are interpreted relative to week -1, making δ_0 the estimate of the causal effect of entry (exit) on retail price. In the same spirit, I employ the Delta Method to convert the coefficients from changes in the price per ounce to fraction changes.

Figure 2.4(a) displays the effect of a new product introduction on an existing product[6]. Four weeks before a new product enters a store, the price gap between adjacent container sizes fell rapidly, dropping by more than 38%. Entry continued this trend, causing a 6% drop in the price gap. The drop in the price gap also continued in the weeks following the new product introduction.

Somewhat different results hold for product exit. Figure 2.4(b) displays an increasing price gap over the 8 week window. In the weeks preceding a product removal, the price gap was 20% lower than in the week before the product was removed. Removing a product, however, has no effect on the price gap between adjacent container sizes. After the product is retired, the price gap continues to increase, yielding a 32% increase in the price gap a month after a product's retirement.

[6]These graphs only display δ. The full regression results are available from the author upon request.

2.5.3 Verifying the Model

The theoretical model described in section 2.2 contains a number of testable predictions that may be used to verify the model's accuracy. First, Lemma 1 suggests that after controlling for the change in the price of the largest size, the introduction (removal) of a container size only changes the prices of smaller container sizes by the same amount, leaving the prices of larger sizes unaffected. To test this prediction, I regress

$$\begin{aligned} \Delta npo_{mst} &= \beta_0 + \beta_1 wpo_{mst} + \beta_2 bundle_m + \delta_v \\ &+ \sum_{l=-4}^{4} \delta_l treat_{lst} + \epsilon_{mst} \end{aligned} \tag{7}$$

where $\Delta npo_{mst} = \frac{price_{mst}}{ounces_m} - \frac{price_{M_j st}}{ounces_{M_j}}$, $\Delta wpo_{mst} = \frac{\text{wholesale price}_{mst}}{ounces_m}$, and M_j indexes the product j's largest container size.

I execute regression 7 four times; the first two regressions examine how the entry and exit of a container size affects larger container sizes of the same product, while the final two examine how entry and exit affect smaller container sizes. Lemma 1 predicts that $\delta_0 = 0$ in the first two regressions and $\delta_0 \neq 0$ in the last two regressions.

The regression results are displayed in figures 2.5 and 2.6. Figures 2.5(a) and 2.5(b) support Lemma 1's prediction. The coefficients are statistically indistinguishable from zero, indicating that the introduction (removal) of container sizes has no effect on the prices of larger container sizes once the price of the largest container size has been accounted for.

Mixed results hold for smaller container sizes. Figure 2.6(a) indicates that the introduction of a new container size lowers prices by 10%, but this result is not statistically significant. Figure 2.6(b) indicates that the removal of a new container sizes raises the price of smaller container sizes by 35%.

I am also able to test a second prediction of the theoretical model; whether the largest container size's price is affected by the introduction (removal) of SKUs. Equations 23 and ?? suggests that 1) the introduction (removal) of an SKU will change the extent that a product covers the horizontal market, and 2) that any changes in a product's horizontal coverage will be reflected in the price of the largest container size. To test these predictions, I regress

$$\begin{aligned} \text{retail price}_{M_j st} = \beta_0 + \beta_1 \text{wholesale price}_{M_j st} + \beta_2 bundle_{M_j} + \delta_v \\ + \gamma_j + \alpha_s + \omega_t \sum_{l=-4}^{4} \delta_l treat_{lst} + \epsilon_{M_j st} \end{aligned} \tag{8}$$

where $M_j st$ denotes the largest container size of product j sold in store s during week t. The estimates of δ_l are displayed in figures 2.7 and 2.8.

Figures 2.7(a) and 2.7(b) examine how the introduction and removal of a container size affects the price of the same product's largest container size. Figure 2.7(a) indicates that the introduction of a new container size decreases the price of the largest container size by 1.8%, while Figure 2.7(b) shows that the removal of a container size has no statistically significant effect on the price of the largest container.

Figures 2.8(a) and 2.8(b), which examine the effect that a product introduction (removal) has on the largest container size of another product, tell a similar story. In both instances, a product introduction (removal) has no significant effect on the price of the largest container size.

Together, these results suggest that the horizontal markets are locally served.

2.5.4 Do Supermarkets Compete Using Sports Drinks?

In order to estimate the causal effect of product entry (retirement) on prices, I must assert that conditional on a store adopting (removing) an SKU, variation in store adoption (removal) times depends on circumstances that are unrelated to that store's characteristics. As I discussed earlier, this assumption can fail for a number of reasons, many of which are accounted for by first-differencing.

Unfortunately, including first differences does not control for two important sources of endogeneity; competition between supermarkets in different chains, and the vertical relationship between Dominick's Corporate and the supermarkets in the Dominick's chain. Dominick's supermarkets that are located near Jewel-Osco supermarkets may face greater competition than supermarkets located farther away, causing these stores to compete by lowering their prices as well as offering their customers additional products. Because my data do not include any information on Jewel-Osco supermarkets, DIFF may mistakenly identify the effect of inter-store competition as the effect of new product introduction on prices.

One way to test whether inter-store competition causes sports drink prices to change is to examine whether a store's revenues change around the time that a sports drink is released (retired). This test is based on the premise that if supermarkets were competing with one another, they would not only compete over sports drinks but over a wide variety of products. If this hypothesis were true, then the introduction or removal of new sports drinks should be accompanied by changes in the supermarket's total revenue. I implement this test by regressing

$$\log\left(revenue_{st}\right) = \beta_0 + \sum_{l=-4}^{4} \delta_l treat_{lst} + \beta_t + \alpha_s + \epsilon_{ist} \tag{9}$$

where $revenue_{st}$ is the total revenue earned by store s during week t, β_t and α_s are the coefficients on store and time dummies, and δ_l are event dummies described earlier.

I estimate 9 using OLS with robust standard errors clustered at the store level, and plot the coefficients on the relative time dummies (δ) against weeks to release (retirement) in figure 2.9. Both plots in figure 2.9 tell a similar story; on average, the release (retirement) of a new product has no significant effect on store revenue. This result implies that inter-store competition is not causing supermarkets to simultaneously change the prices on sports drink container sizes *and* introduce (remove) sports drinks[7].

2.5.5 Is The Delay In Product Adoptions and Retirements Exogenous?

In section 2.3, I described how the Dominick's chain determines which products individual stores will carry. I also described how the chain groups stores into pricing zones and sets different product prices across zones. If the Dominick's chain also determines the order in which products are introduced and removed from stores, and that decision is based upon time-varying, store-specific characteristics, then the order in which stores introduce (remove) products will not be exogenous and the relative time dummies in equation 6 will not identify the effect of product entry or retirement.

To test whether the Dominick's chain determines the order in which store receive or remove products, I regress

$$\Delta mode_{ms} = \beta X_s + \gamma_z + \epsilon_{ms} \tag{10}$$

[7] I also estimate 9 using only bottled sales as a dependent variable. The results are qualitatively similar to those described above.

where $\Delta mode_{ms}$ is the deviation from the modal week in which product m enters (exits) the Dominick's chain, X_s is a vector of demographic coefficients (including an intercept) specific to customers who shop at store s, and γ_z is the coefficient on zone dummy z.

I estimate 10 using OLS with standard errors that are clustered by store and report the results in table 2.5. The second column in table 2.5 reveals that with the exception of a market size measure, none of the store demographics are significantly associated with the arrival (departure) weeks of a sports drink product. The coefficient on the market size measure suggests that stores embedded in larger markets also adopt sports drinks later. The third column yields similar results for retired products.

The results in table 2.5 indicate that the Dominick's chain zone pricing policies do affect the order in which stores receive or retire sports drinks. The second column suggests that stores in zones 10, 12, and 14 typically receive new sports drink products a week after stores in other zones. The third column suggests a similar story; stores in zones 11, 12, 14, and 16 typically hold on to products longer, whiles stores in zone 13 tend to be the first to retire a product.

These results indicate that Dominick's zone pricing strategy is closely tied to the order in which products are introduced or retired. Although store fixed effects do capture Dominick's zone pricing strategy, the fact that the Dominick's chain does choose the order in which products enter and leave stores suggests that other, unobserved factors may play a role in the chain's decision.

2.6 Identifying Substitutes

As discussed earlier, the DIFF strategy presented above will understate the effect of product entry (exit) on existing products if entrants (retirees) affect some products differently than others. This flaw may be formulated as an omitted variables problem

$$\begin{aligned} E[\Delta ppo_{mst}|X] = {} & \beta_0 + \beta_1 \Delta cpo_{mst} + \beta_2 bundle_m + \delta_v \\ & + \beta_3 sub_{mst} + \sum_{l=-4}^{4} \delta_l (treat_{lst} \times sub_{mst}) \end{aligned} \tag{11}$$

where X is the set of regressors and sub_{mst} is a dummy variable equal to 1 if either SKU m or $m+1$ are affected by a product introduction (removal) and 0 otherwise. Equation 11 is identical to the conditional expectation estimated using equation 6, except that it uses sub_{mst} to distinguish SKUs affected by a product's introduction (removal) from those unaffected.

Unfortunately, sub_{mst} is unobserved. Averaging $E[\Delta ppo_{mst}|X]$ over sub_{mst} yields

$$\begin{aligned} E[\Delta ppo_{mst}|X'] = {} & \beta_0 + \beta_1 \Delta cpo_{mst} + \beta_2 bundle_m + \delta_v \\ & + \beta_3 Pr(sub_{mst}) + \sum_{l=-4}^{4} \delta_l (treat_{lst} \times Pr(sub_{mst})) \end{aligned} \tag{12}$$

where X' is the set of regressors excluding sub_{mst} and $E[sub_{mst}|X'] = Pr(sub_{mst})$.

Equation 12 suggests that the omitted variables problem may be solved by including an estimate of $Pr(sub_{mst})$ in regression 12. If I assume that consumers only purchase a single SKU, then $Pr(sub_{mst})$ equals the fraction of customers who switch from an existing SKU m to the new product, or from an exiting product to SKU m. In other words, the probability that two products are substitutes is nothing more than the probability that a consumer will switch between those products.

I estimate these choice probabilities by parameterizing consumer utility and assuming the error term in the utility function follows a Gumbel distribution. These assumptions allow me to estimate the utility parameters using the grouped data random coefficient multinomial logit estimator described in Berry, Levinsohn, and Pakes (1995). Numerous studies employ this estimator because of its economy; as Berry (1994) points out, even simple linear demand system with J products require the econometrician to estimate J^2 parameters. The multinomial logit estimator remedies this problem by translating the econometrician's problem into characteristic space which has a smaller dimension than product space.

This economy comes at a cost. Controlling for endogeneity when using the multinomial logit is difficult. Although Berry, Levinsohn, and Pakes's popular two-step estimator accounts for certain forms of endogeneity, their algorithm may not converge if the econometrician happens to choose poor starting values. To remedy this, I estimate demand using Romeo (2007)'s Bayesian adaptation of Berry, Levinsohn, and Pakes's two-step estimator. The Bayesian method has one great advantage over other methods; because it returns the joint distribution of model coefficients in the sample rather than just the distribution's moments, it is more robust to the choice of initial values.

2.6.1 A Discrete Choice Demand Model

Suppose that shopper i visiting store s during week t can choose to consume one of product $j \in J_{st}$'s M_j sports drink SKUs sold in store s during week t . The shopper earns (indirect) utility

$$V_{imst} = \gamma_i x_m + \beta_i sale_{jst} + \phi_f + \alpha(income_i - price_{mst}) + \xi_{mst} + \epsilon_{imst} \tag{13}$$

$$\begin{pmatrix} \gamma_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \gamma \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i \tag{14}$$

from purchasing SKU $m \in M_j, \forall j \in J_{st}$. Included in the utility function is x_m, a vector of SKU-specific variables that contains information on an SKU's size, as well as brand and size-brand interactions. Also included in the utility function is $sale_{mst}$, a dummy variable equalling 1 if SKU m is on sale. The coefficients on these variables, γ_i and β_i, are random and are included to capture the horizontal and vertical taste variation described in section 2.2. The behavior of these random coefficients is governed by equation 14, which decomposes a consumer's marginal utility into three components; $\begin{pmatrix} \gamma \\ \beta \end{pmatrix}$, common to all consumers, Π, a 7×4 matrix of coefficients that captures the interaction between a vector of consumer-specific demographic variables D_i with x_m and $sale_{stm}$, and Σ, a 7×7 diagonal matrix that captures a consumer's idiosyncratic tastes for x_j and $sale_{stm}$. The vector D_i consists of simulated draws from the store-level joint distribution[8] of a consumer's age, race, education, and number of housemates. The vector v_i is simulated using independent draws from a standard multivariate normal distribution. D_i and v_i are assumed to be independent of one another.

The utility function also contains $income_{ist} - price_{smt}$, which represents a consumer's total expenditure on all other products, and ϕ_f a dummy variable indicating the SKU's flavor. α represents the marginal benefit to a typical consumer from consuming an extra dollar of the outside option and is predicted to have a negative sign.

[8]Unfortunately, the Kilt's marketing center only includes the store-level marginal distribution of these consumer characteristics. I employ the GMM procedure described in Romeo (2005) to parametrically estimate the store-level joint distribution.

Likewise, ϕ_f represents the benefit that a typical consumer receives from purchasing an SKU of a particular flavor.

Berry (1994) advocates including ξ_{mst} in the utility specification to capture SKU characteristics that are unobserved by the econometrician but might be correlated with either prices, sales or the vector of SKU dummies x_m. ξ_{mst} can include unobserved SKU characteristics like sports tops, time dependent characteristics like chain advertising expenditures, or store dependent characteristics like shelf placement. To see this more formally, suppose $\xi_{mst} = \xi_m + \xi_s + \xi_t + \Delta\xi_{mst}$. This specification decomposes unobserved SKU characteristics into an SKU-specific component (ξ_m), a store-specific component (ξ_s), a week-specific component (ξ_t)and a store-week-SKU interaction term $\Delta\xi_{jst}$.

While the dummies described above capture ξ_m, they do not capture demand shocks embodied in ξ_t or promotional activities embodied in $\Delta\xi_{mst}$. Since demand shocks are correlated with promotional activities and prices, without additional controls the estimates of γ_i, β_i will be biased.

I employ two different remedies to control this endogeneity problem. First, I instrument for ξ_s by including zone-level dummy variables as instruments. These zone level variables account for store level decisions that are constant over time, as well as allow for correlation between stores in the same pricing zone. Second, I instrument for store-week-SKU interaction term $\Delta\xi_{mst}$ by including a wholesale price measure.

Finally, the utility model includes ϵ_{istm}, the random component which in a multinomial logit model is iid and follows a Gumbel distribution. This distributional assumption is useful because when combined with the assumptions that a shopper chooses the sports drink that maximizes utility, this distribution yields a partially closed-form solution for the probability that SKU m is chosen

$$\begin{aligned}
\mathcal{S}_{mst} &= \int 1(V_{imst} > V_{ihst}, \forall h \neq m) dP(e, v, D) \\
&= \int \frac{\exp(\gamma_i x_m + \beta_i sale_{mst} + \phi_f - \alpha price_{mst} + \xi_{mst}) dP(v) dP(D)}{1 + \sum_{j=1}^{J_{st}} \sum_{h=1}^{M_j} \exp(\gamma_i x_h + \beta_i sale_{hst} + \phi_f - \alpha price_{hst} + \xi_{hst})} \\
&= \int \frac{\exp(\delta_{mst} + \mu_{imst})}{1 + \sum_{j=1}^{J_{st}} \sum_{h=1}^{M_j} \exp(\delta_{hst} + \mu_{ihst})} dP(v) dP(D)
\end{aligned} \tag{15}$$

where $1(\cdot)$ is an indicator function and

$$\delta_{mst} \equiv \gamma x_j + \beta sale_{mst} + \phi flavor_j - \alpha price_{mst} + \xi_{mst}, \tag{16}$$

$$\mu_{imst} \equiv [x_m, sale_{mst}](\Pi D_i + \Sigma v_i). \tag{17}$$

Because $\sum_{j=1}^{J_{st}} \sum_{m=1}^{M_j} \mathcal{S}_{mst} = 1$, the coefficients on all but one of the SKUs are identified. The traditional solution to this problem is to identify an "outside option", or alternative product that wasn't chosen, and set all the coefficients for this good equal to zero. Doing so implies that coefficients on the other SKUs are measured relative to the outside good. Here, I use the difference between the number of customers who visit a store in a week and the number of sports drink SKUs sold in that store during that week. Under the assumption that each customer who visits the store only purchases a single sports drink SKU, this difference measures the number of consumers who chose not to purchase sports drinks that week.

2.6.2 The Bayesian Method

I use the Bayesian method described in Romeo (2007) to estimate the parameters in equation 15. The Bayesian Estimator is based on the two-step GMM Estimator described in Berry et al. (1995). Berry et al.'s estimator solves for the model parameters that minimize the distance between an SKU's actual and predicted market shares. To accomplish this, Berry et al. choose values for the parameters in equation 15, and use simulated draws from the distributions of D_i and v_i to calculate the choice probabilities in 15. They then employ a contraction mapping to solve for the $\delta_{st} = \{\{\delta_m\}_{m=1}^{M_j}\}_{j=1}^{J_{st}}$ that minimizes the difference between the observed and predicted shares. The second step in Berry et al.'s estimator uses δ_{st} and equation 16 to form the GMM estimator

$$\sum_s \sum_t \xi'_{st} z_{st} A z'_{st} \xi_{st} \tag{18}$$

where $\xi_{st} = \{\{\xi_m\}_{m=1}^{M_j}\}_{j=1}^{J_{st}}$, A is any positive semi-definite matrix, and z_{st} is the vector of instruments described above. Berry et al. repeat the above algorithm using different parameter values until a local minimum is found.

Romeo's algorithm differs from the two-step estimator described above in two ways. First Romeo adopts a Bayesian framework, treating the parameters $\Psi = (\gamma, \alpha, \beta, \phi_f, \Pi, \Sigma, \sigma_\xi, \rho)$ as random variables rather than fixed numbers. Second Romeo replaces the identifying assumption $E[\xi'_{st} z_{st}] = 0$ in equation 18 with $\xi'_{st} z_{st} \sim N(0, \sigma_\xi^2 z'_{st} z_{st})$. This assumption allows Romeo to sample from the joint distribution of Ψ using a hybrid MCMC estimator. Appendix II.B describes Romeo's hybrid estimator in detail.

With these draws from the joint distribution of Ψ in hand, I use the means of the marginal distributions for my analysis. While comparable to the GMM estimates produced by Berry et al.'s two-step estimator, these means will differ for two reasons. First, the distribution assumption on $\xi'_{st} z_{st}$ is stronger than the moment assumption made by Berry et al., and this will lead to inconsistent estimates if incorrect. Second, the Bayesian estimator involves the selection of Bayesian priors that reflect the econometrician's beliefs about the parameter values prior to beginning the study.

These priors can influence the shape of Ψ's distribution, leading to different results.

Nevertheless, the Bayesian method has some advantages over Berry et al.'s estimator. First, while both methods employ the GMM objective function in equation 18, only Berry et al. attempts to find the objective function's mode. The numerical procedures for locating the mode can fail, particularly when the objective function has either many local minima or flat regions. This problem manifests itself as the "sensitivity to initial conditions" issue, where the initial values used in the numerical minimization procedures often determine whether the function's mode is actually reached. In contrast, the Bayesian method integrates over the distribution of Ψ to form an estimator. While this estimator may not be informative, it is certainly computationally feasible. Second, the standard errors of particular model artifacts, such as demand elasticities, are difficult to calculate using Berry et al.. These standard errors, however, are simple to calculate using the joint distribution of Ψ.

2.6.3 Revisiting Differences-in-Differences

With the utility parameter estimates in hand, I can derive the probability that consumers switch from an existing SKU to a new product, or the probability that consumers switch from an exiting product to one of the remaining SKUs. Let N_{st} denote the set of SKUs belonging to an entering product. If consumer utility is approximated by the utility function described in equation 13 then the probability that a consumer switches to a new product is

$$
\begin{aligned}
Pr(sub_{mst}|\text{Entry}) &= \int 1(V_{imst} < V_{inst} \text{ or } V_{i(m+1)st} < V_{inst}, \forall n \in N_{st}) dP(e, v, D) \\
&= \int \frac{\sum_{n \in N_{st}} \exp(V_{inst})}{\exp(V_{imst}) + \sum_{n \in N_{st}} \exp(V_{inst})} dP(v) dP(D) \\
&+ \int \frac{\sum_{n \in N_{st}} \exp(V_{inst})}{\exp(V_{i(m+1)st}) + \sum_{n \in N_{st}} \exp(V_{inst})} dP(v) dP(D). \qquad (19)
\end{aligned}
$$

In other words, the probability that either SKU m or SKU $m+1$ is a substitute for an SKU belonging to a new product n is the probability that consumers prefer $n \in N_{st}$ to either m or $m+1$.

Now, let L_{st} denote the set of SKUs belonging to a retired product. Then the probability that a consumer switches to an existing product is

$$
\begin{aligned}
Pr(sub_{mst}|\text{Exit}) &= \int 1(V_{imst} \geq V_{ihst} \text{ or } V_{i(m+1)st} \geq V_{ihst}, \forall h \notin L_{st}) dP(e, v, D) \\
&= \int \frac{\exp(V_{imst}) + \exp(V_{i(m+1)st})}{1 + \sum_{h \notin L_{st}} \exp(V_{ihst})} dP(v) dP(D). \qquad (20)
\end{aligned}
$$

In other words, an existing SKU is a substitute for an exiting product only if it is preferred to all the remaining SKUs.

Equation 12 can be rewritten as

$$
\begin{aligned}
\Delta ppo_{mst} &= \beta_0 + \beta_1 \Delta cpo_{mst} + \beta_2 bundle_m + \delta_v \\
&+ \beta_3 \widehat{Pr}(sub_{mst}|Entry) + \sum_{l=-4}^{4} \delta_l (treat_{lst} \times \widehat{Pr}(sub_{mst}|Entry) + \epsilon_{mst} \qquad (21)
\end{aligned}
$$

for SKUs exposed to a new product and

$$
\begin{aligned}
\Delta ppo_{mst} &= \beta_0 + \beta_1 \Delta cpo_{mst} + \beta_2 bundle_m + \delta_v \\
&+ \beta_3 \widehat{Pr}(sub_{mst}|Exit) + \sum_{l=-4}^{4} \delta_l (treat_{lst} \times \widehat{Pr}(sub_{mst}|Exit)) + \epsilon_{mst} \qquad (22)
\end{aligned}
$$

for SKUs exposed to a retired product. $\widehat{Pr}(sub_{mst}|\cdot)$ is the estimated probability described in equations 19 and 20, where the estimates are obtained from the Bayesian method described in section 2.6.

2.6.4 Results

The Discrete Choice Model

Because utility function described in equation 13 contains brand fixed-effects as well as brand-volume interactions, I restrict my analysis to those store-week pairs where multiple sizes of each brand are sold. This restriction leaves 263 store-week pairs and 6,424 observations for analysis. Estimation results for the coefficients on brand, size, sales and price, as well as brand- size interactions are reported in table 2.6. Care should be taken in interpreting the standard deviations; the posterior distributions of the coefficients are not normally distributed, meaning that the standard t-test cannot be applied.

The first column in table 2.6 reports γ, β and α, the marginal effects of prices, brands, sizes, and sales that are common to all consumers. The signs of these coefficients are largely as expected; consumer utility increases with the introduction of new brands and decreases when prices increase. Moreover, the results indicate that customers favor receiving discounts on sports drinks. The one incongruency is the sign of the Volume coefficient, which predicts that consumers value larger container sizes.

Also of interest are the coefficients on the brand-volume interaction terms. These coefficients indicate that consumers typically prefer smaller sizes of All-Sport and Powerade to larger ones. More importantly, these results belie the theoretical assertion that the horizontal and vertical dimensions are separable.

The remaining columns present the random coefficients Σ and the demographic interactions Π. These columns reveal that All-Sport is relatively more popular amongst non-whites, senior citizens and the college educated, but less popular amongst larger households and non-whites. Unlike All-Sport, Powerade is relatively unpopular amongst seniors as well as the college-educated, but popular amongst larger households and non-whites. These columns also show that discounts on sports drinks attract larger households and senior citizens, but non-whites and the college educated.

Differences in Differences

I estimate equations 21 and 22 on the 263 store-week pairs used in the Bayesian estimation. Since these regressions contain the generated regressor $\widehat{Pr}(sub_{mst}|\cdot)$, heteroskedasticity-adjusted standard errors do not consistently estimate the true standard error. I remedy this problem by bootstrapping the standard errors and clustering them by SKU and week[9].

To better compare the results, I first estimate equations 21 and 22 without the choice probabilities and display the marginal effects[10] in figure 2.10. Figure 2.10(a) yields qualitatively different results to those from the entire sample; the introduction of a new product on average raises the price gap between adjacent container sizes. The magnitude of the result is also markedly different. Figure 2.10(a) indicates that a product introduction typically caused the price gap to rise by 65%, while the full-sample results indicate the price gap fell by 6%. A similar pattern holds for product exit. Figure 2.10(b) indicates that the price gap rose by 62%, while the full-sample results indicate that the price gap was unaffected by exit.

[9] The bootstrap resamples 50 observations per cluster.

[10] According to equation 12, the causal effect is

$$E[\Delta ppo_{mst}|treat_{0st} = 1] - E[\Delta ppo_{mst}|treat_{-1st} = 1] = \delta_0 Pr(sub_{mst}).$$

As such, the OLS estimates and standard errors from equations 21 and 22 must be weighted by the appropriate selection probabilities. In both cases, I weight the OLS estimates by the median probability.

With the baseline results established, I estimate equations 21 and 22 and display the results in figure 2.11. Figure 2.11(a) indicates that once the selection probability is included, entry causes the price gap to rise by 30%, which is not statistically distinguishable from the 62% decrease found in the earlier analysis.

The same isn't true for product exit. Figure 2.11(b) demonstrates that exit causes the price gap to increases by 26%, which is significantly different from the 65% increase found using the old specification.

2.7 Conclusion

Do firms with market power sacrifice their ability to price discriminate in favor of introducing new products? The theoretical model developed in section 2.2 indicates that a trade-off between discrimination and differentiation only occurs if either consumers who prefer smaller sizes also prefer a particular product characteristic, or if shelving space is scarce.

Using supermarket-level data on sports drinks, I first establish that stores engage in horizontal differentiation as well as price discrimination. I then investigate the effect of product entry and exit on the price schedule of existing products to determine whether stores exchange some of their ability to price discriminate for the ability to differentiate. Sports drinks are well-suited for this study because i) their product characteristics are observed in the data and ii) a number of new sports drinks enter stores over the course of the sample.

I employ a difference-in-differences strategy to investigate this model. I discover evidence supporting the notion that firm's with market power exchange discrimination for differentiation. This evidence directly refutes the the predictions of the theoretical model and suggest that consumer tastes for discrimination and differentiation are related to one another.

My results closely match results from the literature on the relationship between competition and price discrimination. This is somewhat surprising since multi-product supermarkets in my study can choose which products to carry as well as how to price these products, theoretically mitigating the trade-off between horizontal differentiation and price discrimination.

Table 2.1: U.S Sports Beverage Market, 1988-1997

Year	**Total Sales (Millions $)**	**All-Sport**	**Gatorade**	**Powerade**
1988	474		Not Aval.	
1989	568		Not Aval.	
1990	676		Not Aval.	
1991	800		Not Aval.	
1992	800		Not Aval.	
1993	875	2.9%	82.4%	5.9%
1994	1000	7.6%	73.8%	10.5%
1995	1240	9.8%	72.3%	12.1
1996	1390	10.2%	72%	12.9%
1997	1480	9.6%	73.1%	14.3%

Figure 2.1: Sample Market Shares, 1989-1996

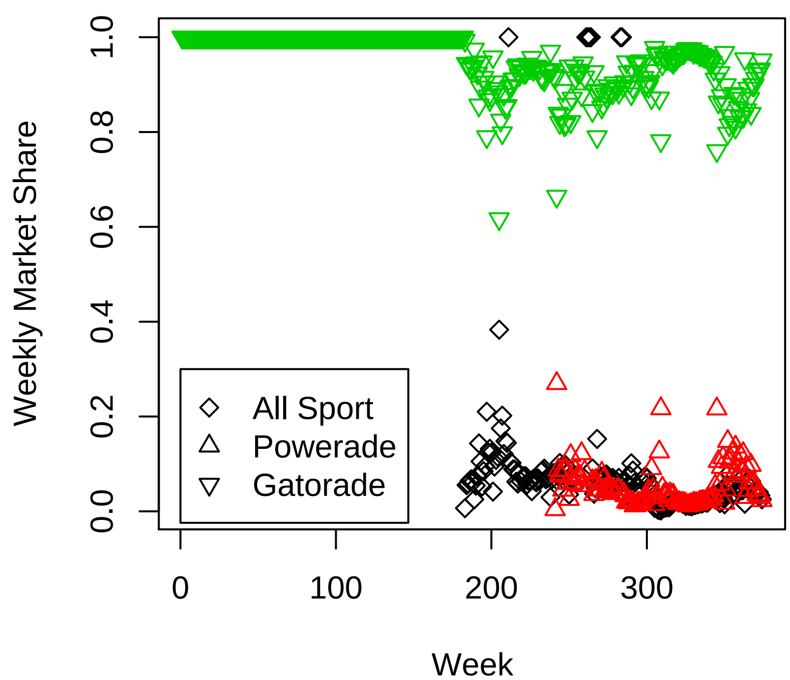


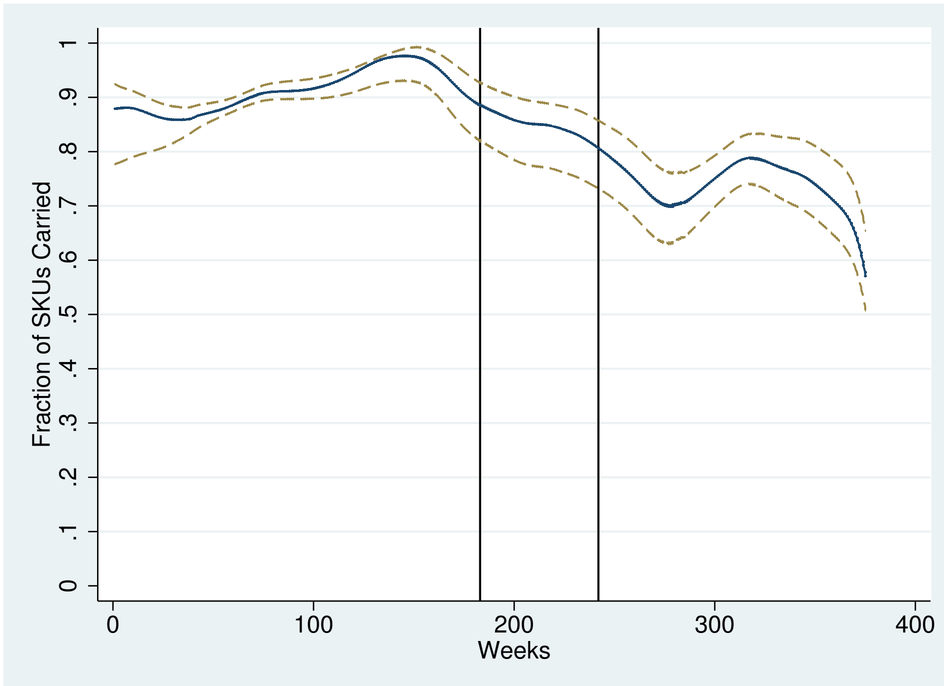
Table 2.2: Sports Drink SKUs Sold By Dominicks

Manufacturer	**Flavor**	**Volume**	**Units Bundled**	**First Week**	**Final Week**
Gatorade	Fruit Punch	16	4	1	41
Gatorade	Fruit Punch	20	1	287	348
Gatorade	Fruit Punch	20	4	337	375
Gatorade	Fruit Punch	32	1	1	375
Gatorade	Fruit Punch	64	1	1	375
Gatorade	Lemonade	16	4	1	53
Gatorade	Lemonade	46	1	1	240
Gatorade	Lemonade	64	1	1	375
Gatorade	Lemon-Lime	16	4	1	196
Gatorade	Lemon-Lime	20	4	335	375
Gatorade	Lemon-Lime	32	1	1	375
Gatorade	Lemon-Lime	46	1	1	292
Gatorade	Lemon-Lime	64	1	1	375
Gatorade	Lemon-Lime	128	1	1	78
Gatorade	Lemon-Lime	128	1	39	375
Gatorade	Orange	16	4	1	39
Gatorade	Orange	32	1	1	375
Gatorade	Orange	64	1	1	375
Gatorade	Orange	128	1	92	375
Gatorade	Citrus Cool	32	1	1	270
Gatorade	Citrus Cool	46	1	1	221
Gatorade	Citrus Cool	64	1	186	375
Gatorade	Lemon Ice	20	4	335	375
Gatorade	Lemon Ice	32	1	1	375
Gatorade	Lemon Ice	128	1	288	375
Gatorade	Tropical Fruit	32	1	82	374
Gatorade	Tropical Fruit	46	1	82	225
Gatorade	Tropical Fruit	64	1	133	375
Gatorade	Tropical Fruit	128	1	294	375
Gatorade	Grape	32	1	126	371
Gatorade	Grape	64	1	132	375
Gatorade	Grape	128	1	290	348

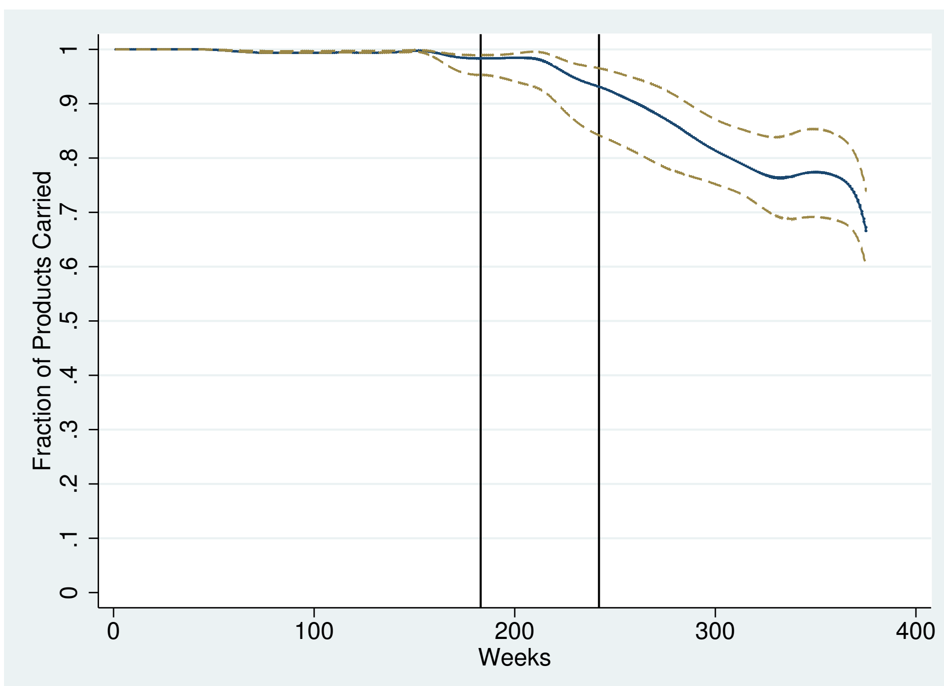
Continued on Next Page…

Manufacturer	Flavor	Volume	Units Bundled	First Week	Final Week
Gatorade	Iced Tea	32	1	186	312
Gatorade	Iced Tea	64	1	184	307
Gatorade	Watermelon	32	1	287	375
Gatorade	Watermelon	64	1	287	375
Gatorade	Raspberry	20	1	287	347
Gatorade	Raspberry	20	4	335	375
Gatorade	Raspberry	32	1	308	375
Gatorade	Raspberry	64	1	336	375
Gatorade	Strawberry Kiwi	20	4	335	375
Gatorade	Cherry	20	4	344	375
All-Sport	Fruit Punch	16	1	290	336
All-Sport	Fruit Punch	16	1	183	297
All-Sport	Fruit Punch	20	1	317	375
All-Sport	Fruit Punch	32	1	183	297
All-Sport	Lemon-Lime	16	1	183	297
All-Sport	Lemon-Lime	20	1	317	375
All-Sport	Lemon-Lime	32	1	183	297
All-Sport	Orange	16	1	183	297
All-Sport	Orange	16	1	290	315
All-Sport	Orange	20	1	309	375
All-Sport	Orange	32	1	183	297
All-Sport	Grape	20	1	309	375
All-Sport	Raspberry	20	1	342	375
All-Sport	Raspberry	32	1	343	375
All-Sport	Cherry	20	1	342	375
All-Sport	Cherry	32	1	343	375
Powerade	Fruit Punch	32	1	242	375
Powerade	Fruit Punch	64	1	249	300
Powerade	Grape	32	1	242	300
Powerade	Grape	64	1	250	300
Powerade	Lemon-Lime	32	1	242	375
Powerade	Lemon-Lime	64	1	249	300
Powerade	Orange	32	1	242	357
Powerade	Mountain Blast	32	1	310	375
Powerade	Tidal Burst	32	1	344	375

Figure 2.2: Fraction Of SKUs And Products Carried By Stores Over Time



(a) SKUs



(b) Products

Table 2.3: Fraction Of Adopters In The Weeks Following A Product Introduction

Manufacturer	Flavor	Adopters	1	2	3	4	5	6	7	8	9	10
Gatorade	Tropical Fruit	80	0.29	0.82	0.94	0.97	1.00	1.00	1.00	1.00	1.00	1.00
Gatorade	Grape	84	0.31	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gatorade	Ice Tea	85	0.01	0.79	0.96	0.98	1.00	1.00	1.00	1.00	1.00	1.00
Gatorade	Watermelon	78	0.28	0.65	0.86	0.88	0.91	0.99	0.99	0.99	1.00	1.00
Gatorade	Raspberry	68	0.81	0.91	0.97	0.99	0.99	0.99	0.99	1.00	1.00	1.00
Gatorade	Strawberry Kiwi	51	0.61	0.86	0.88	0.94	0.94	0.96	0.98	0.98	1.00	1.00
Gatorade	Cherry	61	0.56	0.72	0.85	0.90	0.93	0.95	0.95	0.95	0.95	0.95
All-Sport	Fruit Punch	73	0.48	0.58	0.68	0.77	0.79	0.82	0.86	0.90	0.97	0.99
All-Sport	Lemon-Lime	73	0.49	0.56	0.67	0.75	0.79	0.82	0.86	0.89	0.97	0.99
All-Sport	Orange	75	0.49	0.60	0.69	0.79	0.83	0.84	0.85	0.91	0.97	0.99
All-Sport	Grape	53	0.09	0.34	0.42	0.51	0.60	0.66	0.72	0.75	0.77	0.83
All-Sport	Raspberry	70	0.30	0.56	0.63	0.67	0.69	0.71	0.74	0.74	0.81	0.84
All-Sport	Cherry	71	0.17	0.37	0.48	0.58	0.65	0.68	0.70	0.75	0.79	0.83
Powerade	Fruit Punch	76	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Powerade	Grape	81	0.90	0.91	0.91	0.93	0.93	0.93	0.96	0.96	0.98	0.99
Powerade	Lemon-Lime	79	0.97	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00
Powerade	Orange	75	0.96	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Powerade	Mountain Blast	68	0.09	0.12	0.13	0.25	0.41	0.47	0.50	0.60	0.60	0.66
Powerade	Tidal Burst	75	0.08	0.24	0.28	0.31	0.32	0.55	0.56	0.59	0.67	0.88
			0.47	**0.68**	**0.75**	**0.80**	**0.83**	**0.86**	**0.88**	**0.89**	**0.92**	**0.94**

Table 2.4: Fraction Of Retirees In The Weeks Preceding A Product Removal

Manufacturer	Flavor	Retirees	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Gatorade	Fruit Punch	15							0.67	0.07	0.07	0.07
Gatorade	Lemonade	44				0.84	0.84	0.82	0.80	0.80	0.07	0.05
Gatorade	Lemon-Lime	16							0.69	0.19	0.19	0.12
Gatorade	Orange	19							0.68	0.68	0.26	0.11
Gatorade	Citrus Cool	57						0.89	0.86	0.86	0.05	0.02
Gatorade	Lemon Ice	31							0.81	0.42	0.35	0.32
Gatorade	Tropical Fruit	46							0.87	0.30	0.26	0.20
Gatorade	Grape	52		0.88	0.88	0.88	0.88	0.87	0.79	0.15	0.12	0.08
Gatorade	Ice Tea	81					0.05	0.04	0.04	0.04	0.04	0.04
Gatorade	Watermelon	34							1.00	1.00	0.09	0.03
Gatorade	Raspberry	28						1.00	0.96	0.36	0.32	0.25
Gatorade	Strawberry Kiwi	62		0.97	0.95	0.94	0.94	0.92	0.82	0.31	0.29	0.18
Gatorade	Cherry	59				0.88	0.88	0.86	0.78	0.10	0.08	0.03
All-Sport	Fruit Punch	69			0.57	0.57	0.57	0.55	0.52	0.25	0.14	0.10
All-Sport	Lemon-Lime	66	0.56	0.56	0.56	0.55	0.55	0.52	0.45	0.12	0.09	0.06
All-Sport	Orange	72			0.49	0.47	0.47	0.46	0.39	0.19	0.14	0.08
All-Sport	Grape	48	0.67	0.67	0.67	0.62	0.62	0.56	0.52	0.38	0.31	0.15
All-Sport	Raspberry	51			1.00	1.00	1.00	0.98	0.92	0.41	0.37	0.20
All-Sport	Cherry	55		0.96	0.96	0.96	0.96	0.95	0.82	0.44	0.31	0.22
Powerade	Fruit Punch	68				0.94	0.94	0.91	0.85	0.19	0.16	0.15
Powerade	Grape	73	0.88	0.86	0.84	0.82	0.82	0.81	0.74	0.67	0.55	0.40
Powerade	Lemon-Lime	61				0.95	0.95	0.93	0.90	0.30	0.28	0.18
Powerade	Orange	80			0.17	0.16	0.07	0.07	0.07	0.06	0.05	0.01
Powerade	Mountain Blast	63				0.95	0.95	0.94	0.86	0.35	0.32	0.24
Powerade	Tidal Burst	59						0.98	0.93	0.29	0.27	0.19
			0.70	**0.82**	**0.71**	**0.77**	**0.72**	**0.74**	**0.71**	**0.36**	**0.21**	**0.14**

Figure 2.3: Price Discrimination In The Sports Drink Market

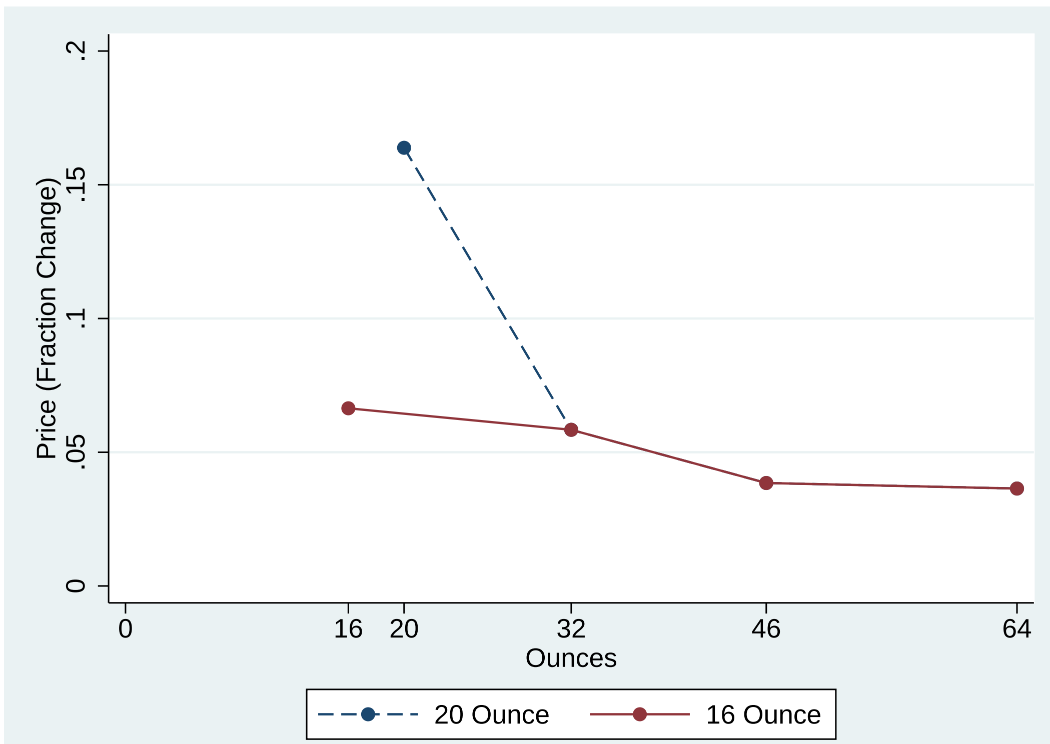
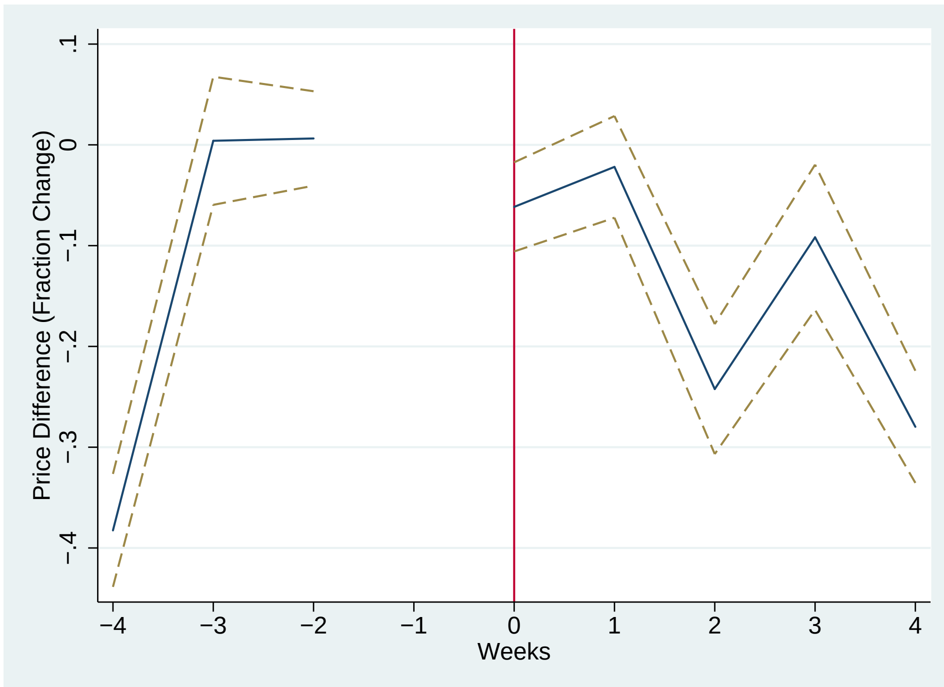
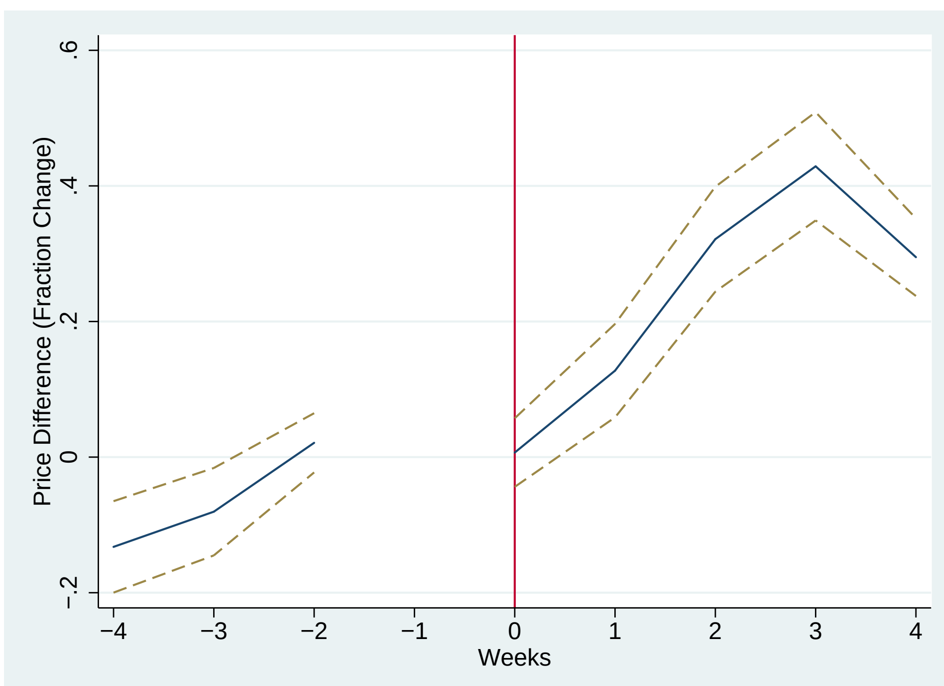


Figure 2.4: Product Entry And Removal

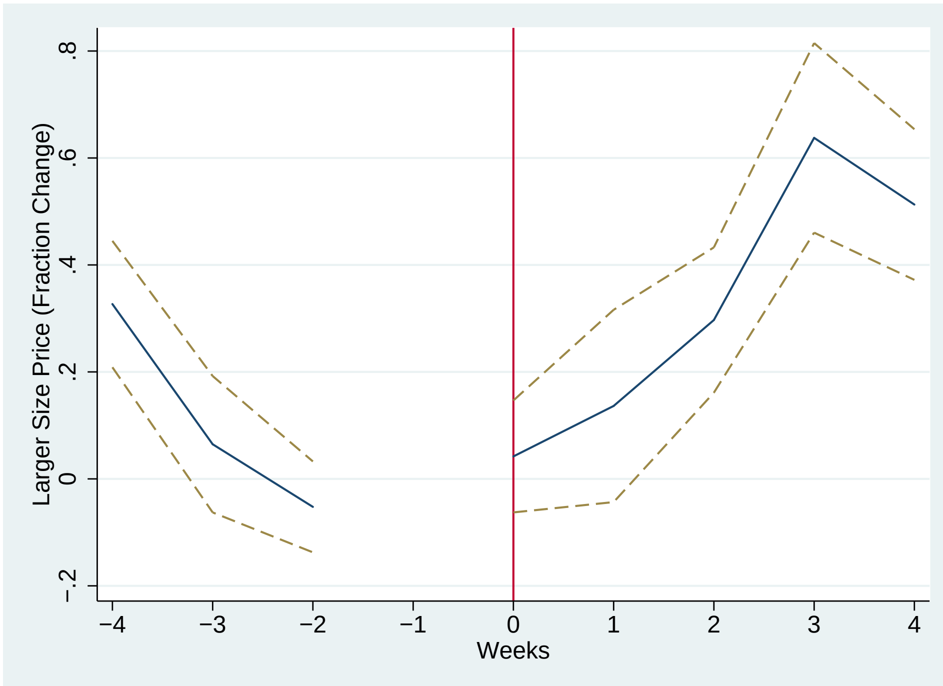


(a) New Product Enters Store

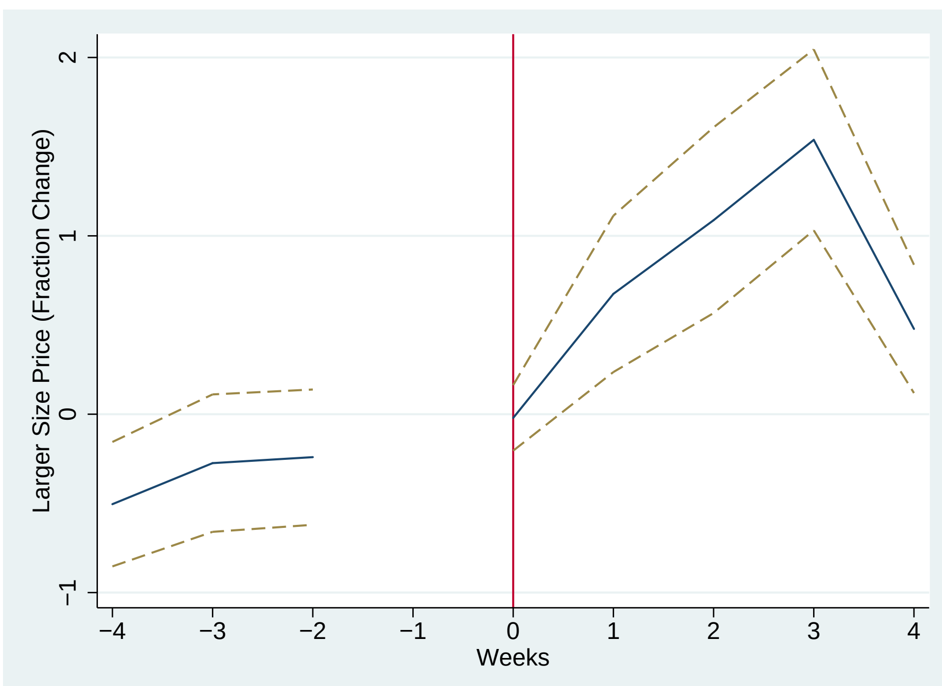


(b) Product Leaves Store

Figure 2.5: The Effect Of Larger Size Entry And Exit

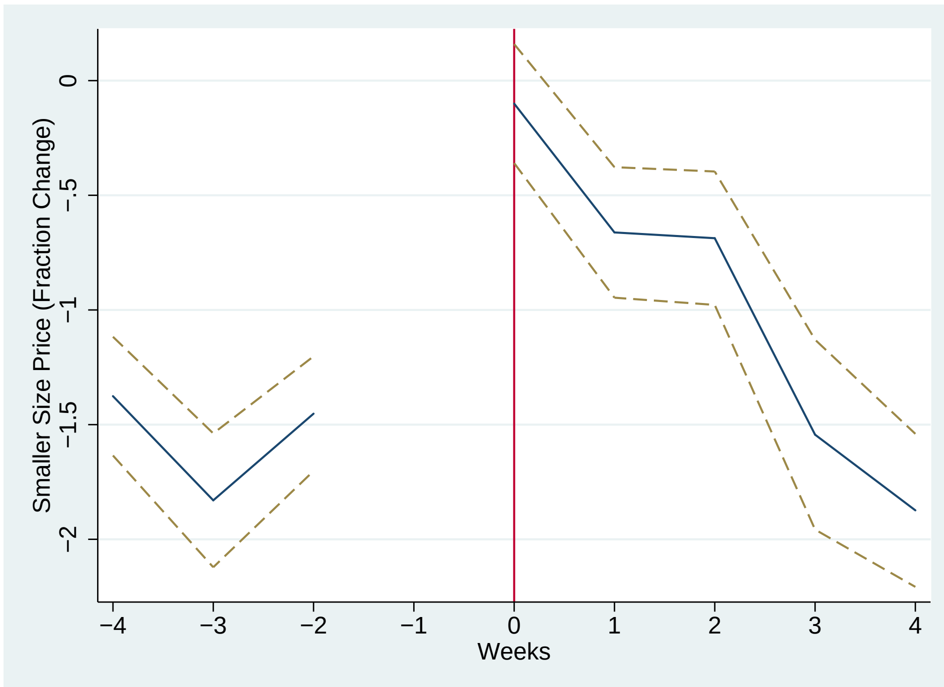


(a) Larger Size Enters

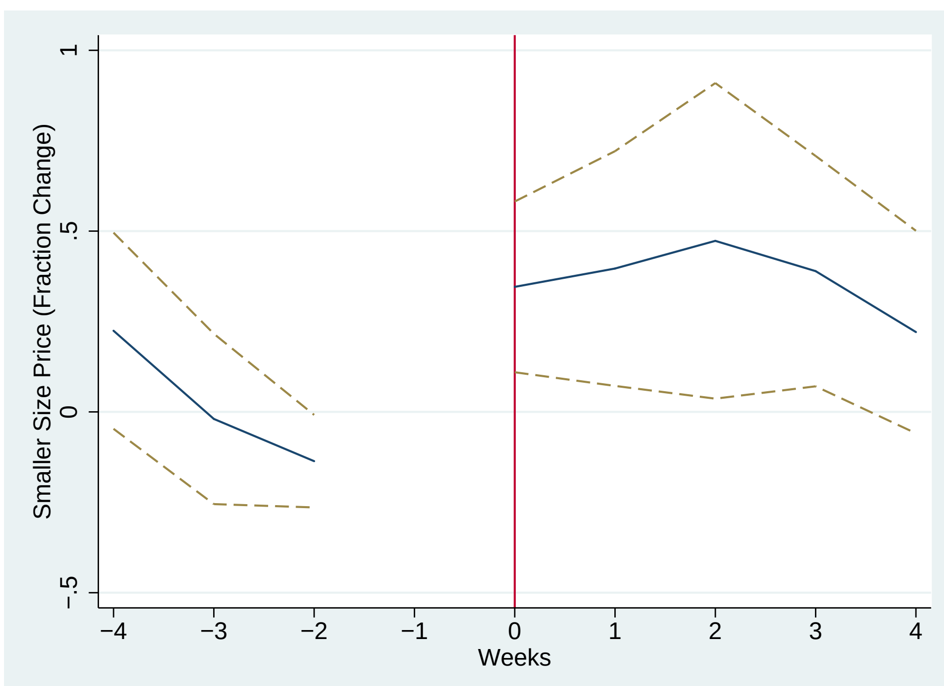


(b) Larger Size Exits

Figure 2.6: The Effect Of Smaller Size Entry And Exit

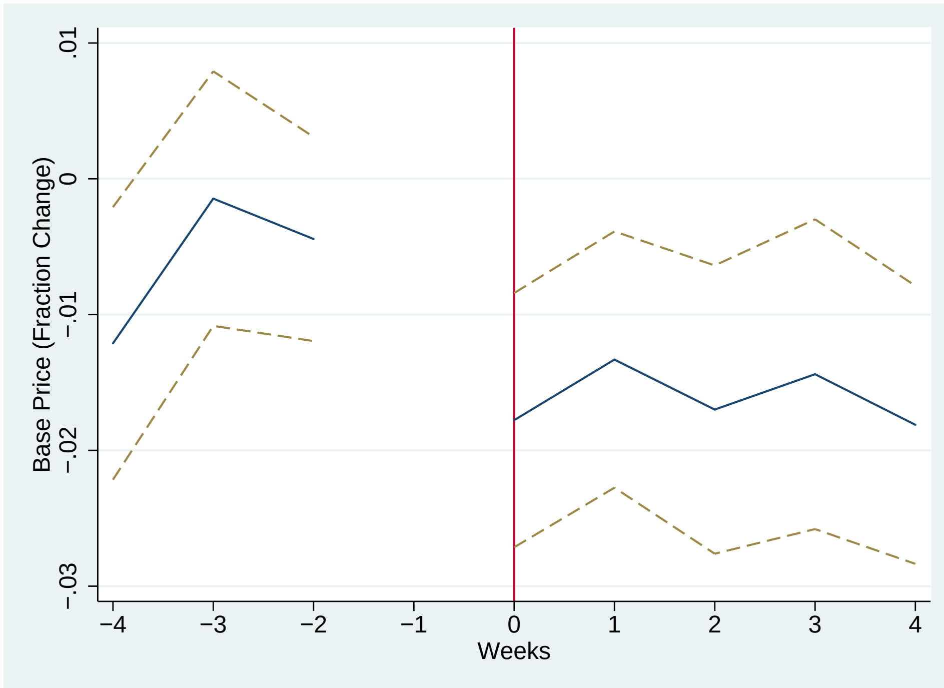


(a) Smaller Size Enters

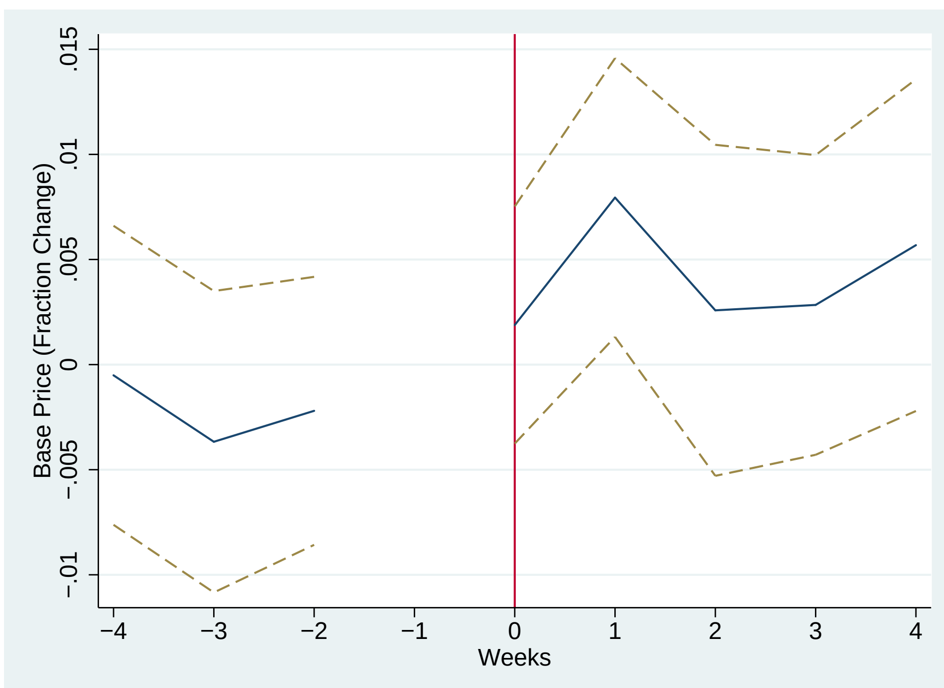


(b) Smaller Size Exits

Figure 2.7: The Effect Of SKU Entry And Exit On The Same Product's Base Price

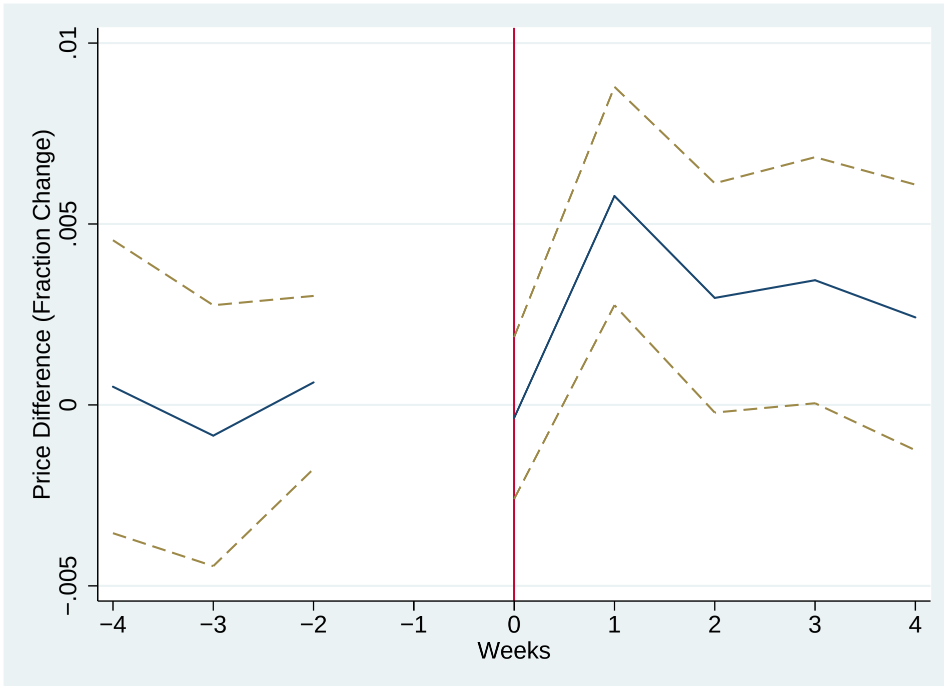


(a) Size Enters

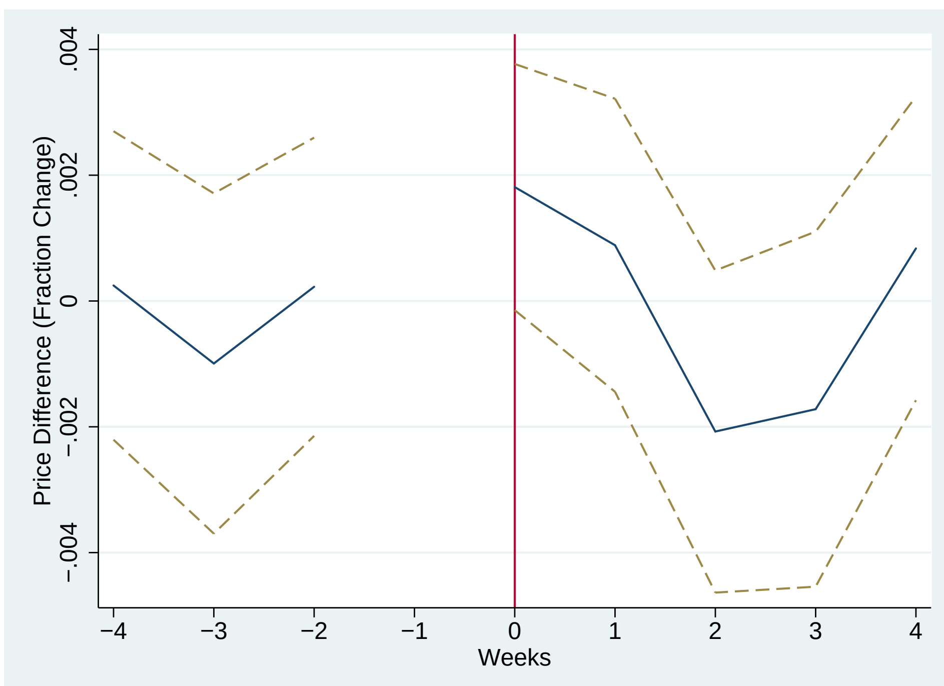


(b) Size Exits

Figure 2.8: The Effect Of Product Entry And Exit On Another Product's Base Price

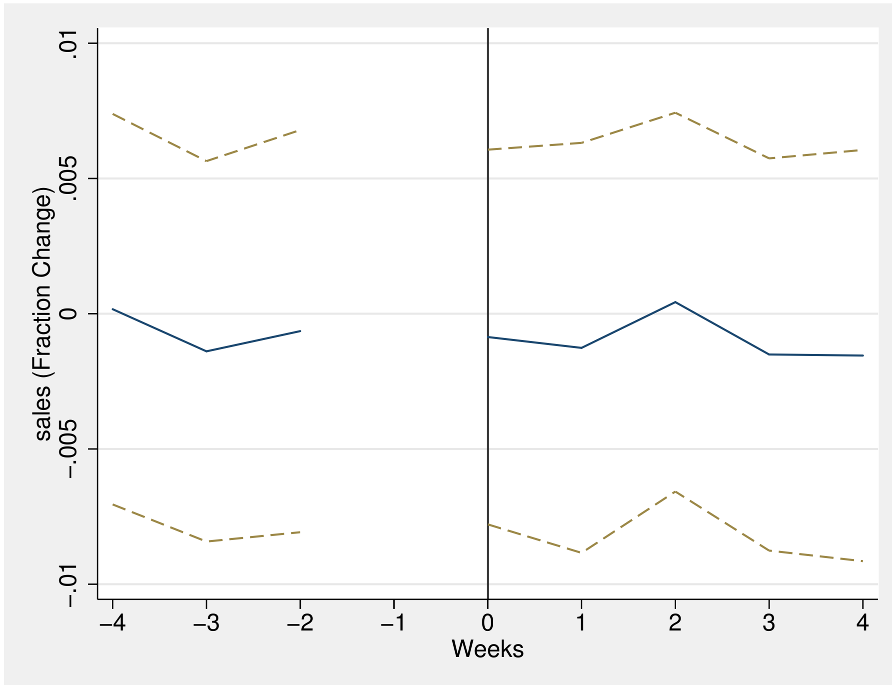


(a) Product Enters

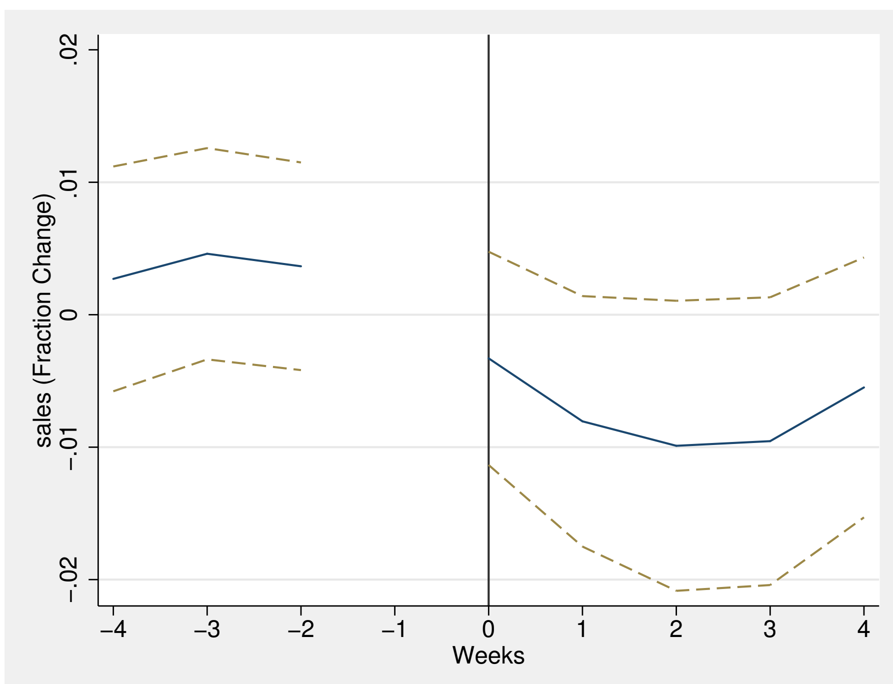


(b) Product Exits

Figure 2.9: The Average Effect Of Sports Drink Entry (Exit) On Store Sales



(a) Entry



(b) Exit

Table 2.5: Sports Drink Rankings Regressions

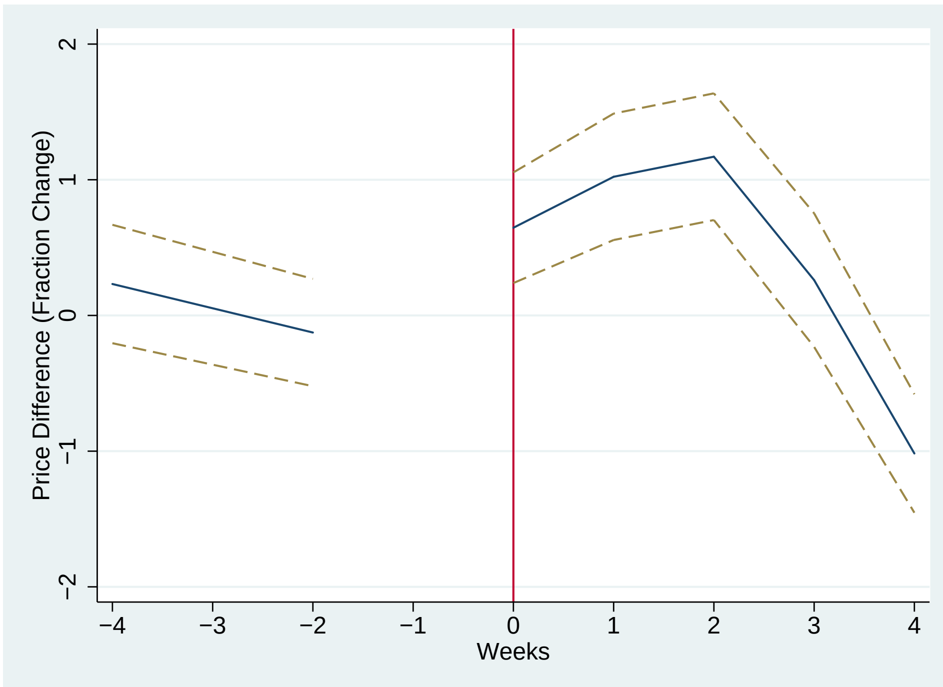
	Weeks from Modal Entry	Weeks from Modal Exit
Log Median Income	0.554	-2.302
	(1.01)	(7.72)
% of Non-Whites	-1.359	-7.248
	(1.31)	(9.87)
Ability to Shop	-1.500	0.386
	(1.68)	(9.52)
Market Sized	0.352**	0.619
	(0.17)	(1.23)
% of Singles	3.270	-82.95*
	(6.48)	(48.6)
% of Retired	-19.75	-44.58
	(14.4)	(92.3)
% of Unemployed	2.745	181.4
	(13.4)	(112)
% Population over age 60	17.16	-10.49
	(16.5)	(104)
% Population under age 9	12.54	-209.5
	(23.0)	(150)
zone 1	-0.0634	-4.991*
	(0.42)	(2.77)
zone 3	-0.342	-0.955
	(0.42)	(3.36)
zone 4	-0.586*	3.069
	(0.32)	(2.20)
zone 5	0.951**	0.289
	(0.39)	(2.89)
zone 6	-0.202	2.556
	(0.50)	(3.77)
zone 7	-0.916	-1.995
	(0.87)	(4.98)
zone 8	-1.120	9.891
	(0.87)	(6.29)
zone 10	0.909**	4.880
	(0.42)	(3.51)
zone 11	-0.279	21.34***
	(0.60)	(4.21)
zone 12	1.287***	10.12***
	(0.33)	(2.17)
zone 13	-0.120	-22.72***
	(0.75)	(5.02)
zone 14	1.032**	15.37***
	(0.42)	(2.83)
zone 15	0.245	7.242*
	(0.81)	(3.94)
zone 16	0.112	10.89***
	(0.43)	(2.73)
Constant	0.407	229.1**
	(12.5)	(97.7)
Observations	1542	1943
R^2	0.06	0.16

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

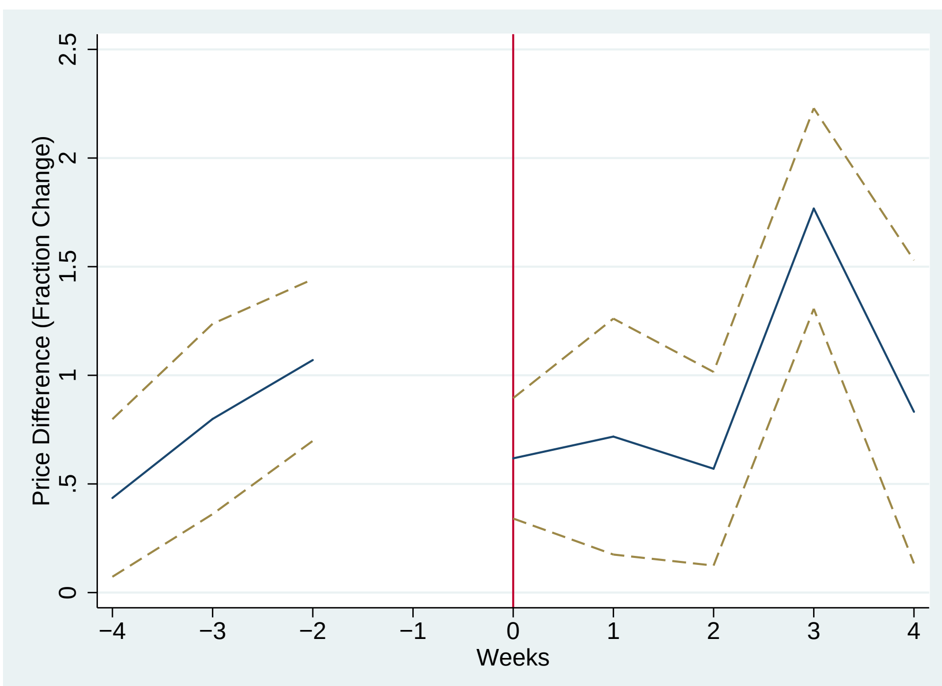
Table 2.6: Selected Coefficients from the Bayesian Model

Variable	γ, β	Σ	# Tenants	Senior	Non-White	College
Intercept	-6.6	0.56	-1.3	-1.6	1	0.42
	(0.56)	(0.17)	(0.5)	(0.5)	(0.15)	(0.29)
Volume	0.076	0.013	–	–	–	–
	(0.0075)	(0.007)				
All-Sport	10	1.4	-0.049	0.85	0.71	1.6
	(0.26)	(0.24)	(0.75)	(0.35)	(0.39)	(0.55)
Powerade	14	1.4	1.7	-3.6	1.9	-1.4
	(0.35)	(0.29)	(0.96)	(3)	(2.8)	(0.58)
Volume $\times$ All-Sport	-0.46	0.19	–	–	–	–
	(0.012)	(0.017)				
Volume $\times$ Powerade	-0.74	0.2	–	–	–	–
	(0.096)	(0.015)				
discount	0.12	0.73	1.9	3.2	-1.7	-1.4
	(0.67)	(0.27)	(0.5)	(0.44)	(0.34)	(0.18)
price	-2.6	–	–	–	–	–
	(0.64)					

Figure 2.10: Product Entry And Removal, Excluding Selection Probabilities

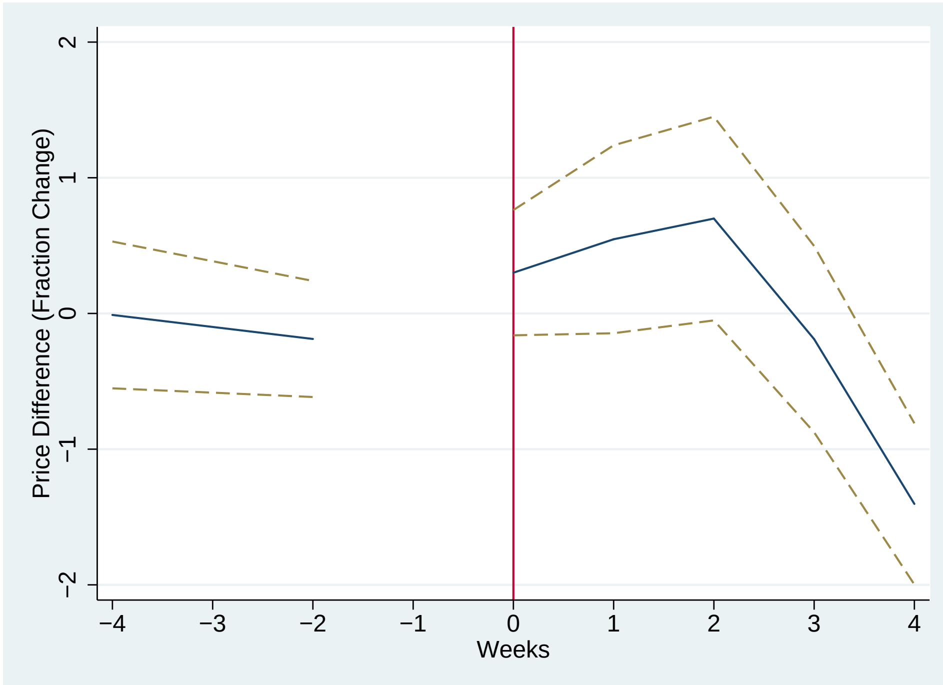


(a) New Product Enters Store

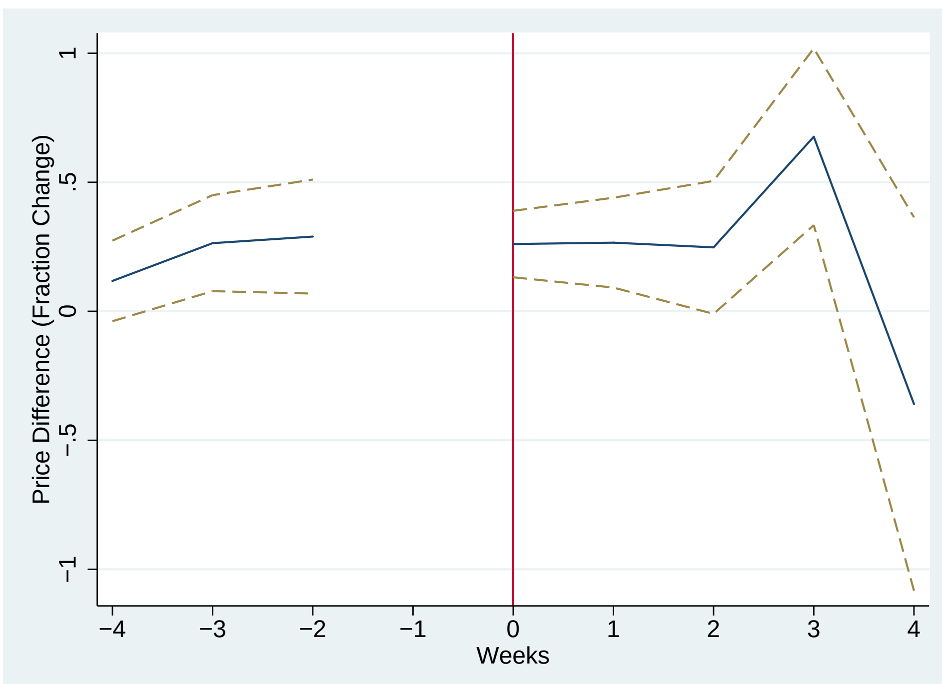


(b) Product Leaves Store

Figure 2.11: Product Entry And Removal, Including Selection Probabilities



(a) New Product Enters Store



(b) Product Leaves Store

II.A The Multi-Product Monopolist

Suppose that a second product is introduced by the monopolist at $\bar{x}$ and this new product is offered in M_2 different quality levels.

Also, assume that the two products have the same number of menu alternatives and that with the exception of the lowest quality level, the quality levels of the new product are identical to those of the old product. The monopolist's problem becomes

$$
\begin{aligned}
&\max_{\mathbf{p}_1,\mathbf{p}_2} \quad E_x[\pi(\mathbf{p},x)|x \leq x_1] + E_x[\pi(\mathbf{p},x)|x \geq x_2] \qquad \Leftrightarrow \\
&\max_{\mathbf{p}_1,\mathbf{p}_2} \quad (p_{M_1} - C_{M_1})\frac{x_1}{\bar{x}(\bar{\theta}-\underline{\theta})}\left[\bar{\theta} - \frac{2p_{M_1}+\tau x_1}{2q_{M_1}}\right] + \\
&\qquad \frac{x_1}{\bar{x}(\bar{\theta}-\underline{\theta})}\sum_{m=1}^{M-1}(\Delta p_m - \Delta C_m)(\bar{\theta}-\theta_m) + \\
&\qquad (p_{M_2} - C_{M_2})\frac{\bar{x}-x_2}{\bar{x}(\bar{\theta}-\underline{\theta})}\left[\bar{\theta} - \frac{2p_{M_2}+\tau(\bar{x}-x_2)}{2q_{M_2}}\right] + \\
&\qquad \frac{\bar{x}-x_2}{\bar{x}(\bar{\theta}-\underline{\theta})}\sum_{n=1}^{M-1}(\Delta p_n - \Delta C_n)(\bar{\theta}-\theta_n)
\end{aligned}
$$

Further, suppose that the horizontal markets for both products overlap[11]. Then there is a customer endowed with horizontal type $x_1 = x_2 = \tilde{x} = \frac{p_{M_1} - \frac{q_{M_1}}{q_{M_2}}(p_{M_1}+\tau\bar{x})}{-\tau(1+\frac{q_{M_1}}{q_{M_2}})}$ who is both indifferent between consuming the two products and not purchasing either product. The multi-product monopolist's problem yields the following conditions[12]:

[11] Specifically, I only consider the case where the base quality variants of both products overlap. It is possible, however, for the base qualities not to overlap, in which case the market is vertically segmented.

[12] I only present the first order conditions for the first product. The conditions for the second product are symmetric.

$$\begin{aligned}
&\tilde{x}\left[\bar{\theta}-\frac{2p_{M_1}+\tau\tilde{x}}{2q_{M_1}}\right]-\frac{p_{M_1}-C_{M_1}}{q_{M_1}}\tilde{x}+\\
&\frac{\partial\tilde{x}}{\partial p_{M_1}}\left[(p_{M_1}-C_{M_1})\left(\bar{\theta}-\frac{p_{M_1}+\tau\tilde{x}}{q_{M_1}}\right)-(p_{M_2}-C_{M_2})\left(\bar{\theta}-\frac{p_{M_2}+\tau(\bar{x}-\tilde{x})}{q_{M_1}}\right)\right]+\\
&\frac{\partial\tilde{x}}{\partial p_{M_1}}\left[\sum_{m=1}^{M-1}(\Delta p_m-\Delta C_m)(\bar{\theta}-\theta_m)-\sum_{n=1}^{M-1}(\Delta p_n-\Delta C_n)(\bar{\theta}-\theta_n)\right]=0 \qquad (23)\\
&\Delta p_m=\frac{\bar{\theta}\Delta q_m+\Delta C_m}{2}, \quad \forall m<M_1 \qquad (24)
\end{aligned}$$

where

$$\frac{\partial\tilde{x}}{\partial p_{M_1}}=-\frac{1}{2\tau}$$

Equation 23 indicates that the base quality level of each product is a function of its own price, the base price of the other product, and the price of all add-ons. This is similar to the first order condition from the single-product case (equation 3), where the base price was only a function of its own price and the price of all its add-ons. Moreover, because of the independence between horizontal and vertical tastes, equation 24 is identical to equation 4; the price gap between adjacent quality levels is unaffected by the introduction of new products.

Proof of Proposition 2. This proposition follows immediately from the fact that equation 24, which determines the equilibrium price for all product add-ons, is independent of all other prices. □

Proof of Proposition 3. Without loss of generality, suppose that prior to the new product introduction, $x_1=\bar{x}$. After the new product is introduced, it must be the case that $x_1=\tilde{x}<\bar{x}$. Since $\tilde{x}$ was available to the monopolist before the new product was introduced, it must be less profitable then setting $x_1=\bar{x}$. □

I employ the following lemma to empirically test some of the model's features.

Lemma 1. *Introducing (removing) a container size q^*, where $q_i > q^* > q_{(i+1)}$, changes the prices of all $q > q^*$ by dp_M and all $q < q^*$ by $dp_M + dp_i$*

Proof. Without loss of generality, only consider the existing product. Equation 23 implies that the introduction of a new size will change P_M. Equation 24 also indicates that the introduction of a new product will only effect Δp_i and $\Delta p^* = p^* - p_{(i+1)}$. Since $p_m = p_M + \sum_{i=m}^{M-1} \Delta p_i$, $\forall m < M$, p_m will change by dp_M if $m < i$ and by $dp_M + dp_i$ if $m \geq i$. Similar results hold for the removal of a container size. □

II.B The Bayesian Method

Suppose that $\xi'_{st} z_{st} \sim N(0, \sigma_\xi^2 z'_{st} z_{st})$. Bayes' Rule yields the joint density of Ψ

$$p(\Psi|, price, sale, x, z) \propto \sigma_\xi^{-JT} \exp\left(-\frac{1}{2\sigma_\xi^2} \sum_s \sum_t \xi'_{st} z_{st} (z'_{st} z_{st})^{-1} z'_{st} \xi_{st}\right) p(\Psi) \quad (25)$$

where $p(\Psi)$ is the prior density of Ψ that must be specified by the researcher.

Since the joint density described above cannot be sampled from directly, Romeo forms a hybrid MCMC estimator by dividing Ψ into three blocks, $\eta = (\gamma, \alpha, \beta, \phi_f)$, σ_ξ^{-2}, and $\Gamma = (\Pi, \Sigma)$ and derives the conditional distributions for the first three blocks using equation 25

$$\eta|r, z, \Psi_{-\eta} \sim N(\overline{\eta}, \Omega_{\overline{\eta}}) \quad (26)$$

$$\sigma_\xi^{-2}|r, z, \Psi_{-\sigma_\xi} \propto G(\frac{JT + \phi_\xi}{2}, ((\delta - r\eta)' P_z (\delta - r\eta) + \phi_\xi \sigma_{\xi_0}^{-2})^{-1})/2 \quad (27)$$

where

$$P_z = z(z'z)^{-1}z', r = (x_j, p_{jst}, sale_{jst}, flavor_f)$$

$$\Omega_{\overline{\eta}} = (\sigma_\xi^{-2} r' P_z r + V_{\overline{\eta}}^{-1})^{-1}, \overline{\eta} = \Omega_{\overline{\eta}}(\sigma_\xi^{-2} r' P_z \delta + V_{\overline{\eta}}^{-1} \overline{\eta}_0)$$

For the final block Γ, Romeo notes that no well known distribution corresponds to Γ so instead implements a random walk Metropolis Hastings algorithm. To do this, he employs a first order Taylor series expansion of $\delta(\Gamma)$ around the current value of Γ to obtain a proposal distribution for Γ

$$\Gamma | r, z, \delta, \Psi_{-\Gamma} \sim N(\Gamma, \Omega_\gamma) \tag{28}$$

where

$$\begin{aligned} \Omega_\gamma &= (\sigma_\xi^{-2} Q(\Gamma)' P_z Q(\Gamma) + V_{\gamma_0}^{-1})^{-1}, \\ Q(\Gamma) &= \frac{\partial \delta(\Gamma)}{\partial \Gamma} \end{aligned}$$

Romeo recommends using the following algorithm to sample from the joint density of Ψ.

1. Choose initial values Ψ^0 and δ^0 for Ψ and δ.

2. Sample $\eta^{(r)}$ from the multivariate normal density described in equation 26, conditional on the most recent values of $\Psi_{-\eta}$ and δ.

3. Sample $\sigma_\xi^{(r)}$ using the Gamma density in equation 27, conditional on $\Psi_{-\sigma_\xi}$ and δ.

4. Sample Γ^{cand} from the multivariate normal proposal distribution described in equation 28.

5. Use Γ^{cand} and $\Psi^{(r)}$ in the contraction mapping to form δ^{cand}.

6. Accept Γ^{cand} with probability

$$\alpha(\Gamma^{cand}, \Gamma^{(r)}) = \min\left\{ \frac{p(\Psi; \Gamma^{cand})}{p(\Psi; \Gamma^{(r)})}), 1 \right\} \tag{29}$$

where $\Gamma^{(r)}$ is the current value of Γ and $p(\cdot)$ is the joint density from equation 25.

7. Repeat steps 2-7 R times, keeping only the $R - b$ draws. Discarding the first b draws allows the Markov chain to throw off the influence of the initial values.

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CHAPTER III

Competition and Price Discrimination in the Market for Mailing Lists

3.1 Introduction

This paper examines the relationship between competition and price discrimination in the market for mailing lists. More specifically, we examine whether list sellers have a higher propensity to segment consumers by offering a menu of choices (second-degree price discrimination) and/or to offer targeted prices to readily identifiable groups of consumers (third-degree price discrimination) in more competitive markets.

While the textbook definition of price discrimination states that price discrimination occurs when "two units of the same physical good are sold at different prices," practitioners have found this definition unsatisfactory Tirole (1988).[1] Instead, they have defined price discrimination as selling similar goods at different prices in order to extract consumer surplus. In his book, Stigler (1987) states that a firm price discriminates when the ratio of prices is different from the ratio of marginal costs for two goods offered by a firm. More recently, Stole (2003) has advanced a broader definition that "price discrimination exists when prices vary across customer segments

[1] While Tirole offers this definition, he very quickly goes on to discuss its shortcomings.

[in a way] that cannot be entirely explained by variations in marginal cost."[2] Our paper uses this definition of price discrimination.

The mail order catalog industry proves to be a useful setting in which to assess the relationship between price discrimination and competition. Because mailing lists are pure information goods, they have zero marginal costs. Hence, any price variation cannot be attributed to cost differences and must therefore be attributed to variations in demand. Furthermore, we posit that pure information goods are likely to exhibit price discrimination: Since one of the necessary conditions for price discrimination - that resale or transfer of the good be limited - is also a necessary condition for a functioning information market, any seller of information goods already has the capacity to discriminate Arrow (1962). We discuss how this resale is prevented in the mailing list industry in Section 3.2.

In the mailing list industry, buyers often have the option of purchasing names from the complete list or selecting names from a subset of the list, called a "select," at a premium for each name. For instance, if a marketer chose to rent only names of female consumers from a given catalog list we would say that they chose a gender select, or if they chose to rent only names of consumers who have purchased over \$100 from that same list then we would say that they chose a dollar select. Typical pricing might have the base list renting for \$70 per thousand names, the gender select for \$75 per thousand and dollar select for \$100 per thousand names. Marketers might choose both a gender select and a dollar select, for example ordering the names of female customers who spent more than \$100; in our example, the marketer would then pay \$105 per thousand names for such a list. Given that all of these products have zero marginal cost for the list owner, the price differences cannot be

[2]See Stigler (1987), Tirole (1988), Varian (1989), Stole (2003), and Clerides (2004) for more detailed discussions.

attributed to cost differences. Thus, this pricing strategy amounts to second-degree price discrimination.

Offering additional selects is similar to expanding the number of products that are offered. As authors including Moorthy (1984) and Johnson and Myatt (2003) have noted, there exists a duality between some forms of second-degree price discrimination and product-line expansion. For example, the decision of how many package sizes to offer can be viewed as either a product line decision or as a price discrimination decision if the purpose of offering the different sizes is to extract consumer willingness-to-pay Cohen (2005). However, Draganska and Jain (2006) demonstrate that not all product-line expansions constitute price discrimination. They find that in the yogurt industry, only vertically-differentiated product line variation can be used for price discrimination, while horizontal product-line expansion generally cannot. Thus, our paper can shed light on how the optimal product line differs with the level of competition to the extent that product lines are being chosen for the purpose of price discrimination.

List owners also offer different prices to identifiable groups of list renters. Most notably, fundraising organizations and charitable organizations are offered lower prices, while marketers selling similar products to those offered by the list owner are charged higher prices. Both of these actions constitute third-degree price discrimination.

Initially, much of the price discrimination literature focused only on price discrimination by a monopolist. However, Katz (1984) and Borenstein (1985) present models that demonstrate that price discrimination can occur in free-entry markets. Shepard (1991) empirically verifies that price discrimination is consistent with competition by showing that that variations in the prices of different grades of gasoline can not be attributed to cost, and thus constitute price discrimination in a fairly competitive market. Similarly, Graddy (1995) finds that third-degree price discrimination occurs even in the very competitive Fulton fish market.

Having established these facts, subsequent research began focusing on the question of how competition affects incentives to price discriminate. The ensuing theoretical literature shows that competition can either increase or decrease the incentives to price discriminate.

One reason why competition can decrease the incentives to price discriminate is that if competition is intense enough then there is little room for firms to price above marginal cost.[3] Further, if there are fixed costs associated with price discrimination - as exist in the mailing list industry - then competition can reduce price discrimination because the number of consumers allocated to each pricing level can become too small to support the fixed costs. This latter effect is modeled by Seim and Viard (2004). These two effects both imply that increased competition makes it more difficult for firms to price discriminate.

However, competition can also lead to increased price discrimination. The first reason is that competition can trigger a prisoner's dilemma where each list pays the sunk costs required for price discrimination, but where all lists would be better off if no lists price discriminated.[4] Such a situation could arise if consumers obtained similar value from each of the products offered by a given firm.[5] In this case, a firm without much competition has low incentives to pay the fixed costs of offering more choices to consumers since any new products simply cannibalize existing sales. However, when there is more competition, firms now have to focus on attracting

[3]Similarly, Stole (1995), Desai (2001), and Rochet and Stole (2002) show that the quality distortion associated with price discrimination can diminish as the level of competition increases.

[4]Such a prisoner's dilemma is at the heart of models by Corts (1989) and Shaffer and Zhang (1995).

[5]While the example in this paragraph uses the language of second-degree price discrimination, similar logic applies for third-degree price discrimination. Instead of offering more menu choices, the firm would target prices for more groups of customers.

consumers from competitors rather than focus on cannibalization. Seim and Viard (2004) demonstrate that this prisoner's dilemma will persist for second-degree price discrimination when the costs of offering consumers more choices is not too expensive.

Competition can also increase the dispersion of willingness-to-pay that any particular firm faces, and thereby increase the incentives to price discriminate. This occurs when there is heterogeneity in the degree to which consumers care about cross-firm product differentiation. Imagine that some consumers are quite sensitive to cross-firm product differentiation, and thus are hesitant to consume from anyone except their ideal firm, while other consumers are relatively indifferent about which firm they patronize. Both types of consumers will generally buy from the local monopolist when there is limited competition, leaving the firm with little incentive to price discriminate. However, when the level of competition increases, firms then have incentives to charge high prices to those consumers who have strong preferences for their product, but low prices to consumers who are not sensitive to product differentiation and therefore treat the firms' goods as undifferentiated commodities. Chen et al. (2001) use a model where some consumers are loyal and some consumers switch between firms to demonstrate this effect for the case of targeted discounts (third-degree price discrimination). Similarly, Dogan et al. (2005) use a model where consumers have different sensitivities to product differentiation to show that rebating (second-degree price discrimination) can become profitable with increased competition.

Because theory alone cannot predict whether price discrimination should increase or decrease with higher competition, we treat the relationship between competition and price discrimination as an empirical question.

Several empirical papers examine the link between competition and price discrimination. For example, Stavins (2001), Busse and Rysman (2005), and Miravete and

Röller (2004) all examine how the curvature of price schedules vary with the level of competition. In all three cases, competition is associated with an increased curvature in the price schedule. While this seems to suggest that there is more price discrimination in more-competitive markets, deeper consideration reveals that it is often hard to tell whether increased curvature should be interpreted as more or less price discrimination. For example, Busse and Rysman's study of the yellow pages advertising market reveals that prices of large ads fall by a greater percentage than those of small ads under increased competition. However, it is unclear whether this should be viewed as increased quantity discounting (more price discrimination) or a move towards marginal cost pricing (less price discrimination). Because of this difficulty in interpretation of the results, these papers are careful not to draw conclusions about whether price discrimination increases with competition.

In a paper that looks at a similar question - the link between competition and price dispersion - Borenstein and Rose (1994) find that airline routes with greater competition exhibit a greater level of price dispersion. Similarly, Asplund et al. (2002) study the newspaper industry and find that newspapers in duopoly markets offer a discount to a greater fraction of their consumers than newspapers in monopoly markets. However, Chintagunta (2002) examines the effect of retail competition on optimal pricing in the analgesics (pain reliever) category and finds that competition leads to lower prices on Tylenol's price, while increasing the store-brand's price. This implies that competition is reducing the amount of price dispersion in that category.

In contrast to these papers, we use a different empirical strategy. Since the marginal cost of all products is zero, we can interpret firms' offering of additional selects at prices different than the price of the base list as price discrimination. We therefore focus on the firm's decision whether to price discriminate (by offering selects), and if so, the firm's choice of the number of options presented to consumers. Examining this decision of whether to price discriminate provides a direct way to measure whether the prevalence of price discrimination is higher or lower in competitive markets.

We know of only one paper that has taken a similar approach. Seim and Viard (2004) study the US cellular telecommunications industry and examine how entry affects the number of pricing tariffs that the firms offer, finding that increased competition leads to a proliferation of calling plans. Our paper differs in a number of important ways. First, we examine both second and third degree price discrimination, while Seim and Viard only examine second degree price discrimination. Further, the type of second degree price discrimination is different in the two papers. Seim and Viard examine second-degree price discrimination in the form of different tariff structures: some consumers may pay different prices, but all consumers who make a call are buying a good of the same quality. In contrast, the second-degree price discrimination that we examine is discrimination of the form of either quality discrimination or mixed bundling.[6] Finally, only a fraction of the firms in our data engage in each of the different types of price discrimination that we observe. Thus, we are able to examine how competition influences a firm's decision whether to price discriminate at all in addition to how competition affects the number of choices offered.

The results indicate that increased competition is generally associated with an increased propensity to price discriminate. These results hold for both second-degree

[6]The similarity to quality discrimination comes from the fact that selects can be viewed as different quality levels: more selective lists allow direct mailers to better target their advertising and should therefore be more valuable relative to the base list. For example, a mailer may be willing to pay more for names of more recent buyers or of buyers who have large purchase amounts, since the prospects may be more likely to respond to the mailer's offer or to spend more, conditional on responding. On the other hand, one could also view this as bundling: purchasing a base list could be viewed as buying a bundled product, at a discount, that includes the male and female buyers from the list owner's catalog.

and third-degree price discrimination. Further, list owners offer menus with more choices in more competitive markets. That is, not only are lists in more competitive segments more likely to price discriminate, they will also partition their consumers into finer subsets. These results, taken together with the many empirical studies summarized above, suggest that the connection between competition and increased price discrimination is a result that applies more broadly. We speculate in the conclusion why this may be the case.

The remainder of this article proceeds as follows. In Section 3.2, we describe the mailing list industry and the data. We also describe our measures of price discrimination and competition. The results are discussed in Section 3.3. Section 3.4 summarizes and discusses the broader implications of our findings.

3.2 Mailing Lists

3.2.1 Industry Capsule: The Mailing List Industry

For over eighty years, businesses have been compiling and trading lists of customers, forming the core of an ever-expanding direct marketing industry.[7] Marketers purchase these lists in order to contact potential customers by mail with information, advertisements, special offers, etc. regarding their products and services. In 1996, the last date for which the authors have been able to find such data, the mailing list industry had sales of roughly $1.7 billion and over 31 billion names were exchanged Borzekowski (1999).

Despite the importance of the direct mail industry, relatively little academic research has been conducted on the industry. Bult and Wansbeek (1995) demonstrates how to optimally target a direct mail campaign. Anderson and Simester (2004) and Simester et al. (2006) examine dynamic issues in mail-order catalogs, studying how

[7]See Burnett (1988) for history and details of the list industry.

current mailings affect future purchase behavior. Finally, Steenburgh et al. (2003) and Füsun and Ter Hofstede (2006) both discuss statistical issues with direct mail data.

Before describing how mailing lists price discriminate, we note that list owners are represented by list managers who handle the sales and marketing of the owner's list. In 1997 there were 150 such managers who advised owners of the catalog lists. Most of these managed a relatively small number of lists - only 25 managed more than 10 lists. List managers generally receive a 10% commission, and work with the list owners to set prices and decide about the selects to be offered. As a result, we treat the decision to price discriminate as a profit-maximizing decision by well informed agents: even small list owners who rent their lists solely for some extra income will price strategically with the help of the list manager.

Second-degree price discrimination is implemented through the use of 'selects,' or subsets of the list. For example, if a mailing list offers a multi-buyer select then the marketer can choose either to rent names belonging to the base list, or to pay a premium and rent only names of consumers who made multiple purchases from the catalog that generated the mailing list. The most common forms of selects that we study include multi-buyer selects, gender selects, dollar selects, recency selects and inquirers-only selects.[8] Recency selects are based upon the timing of the last purchase that the rented name made from the underlying catalog, while the inquirers-only selects provide names of people who have asked for a catalog but never made a purchase. Because the timing of recency selects vary across the different lists, we created a tag of 'Vintage Names Available' which we applied to all catalogs that offered names of consumers who had last made a purchase from their catalog more

[8]Almost all lists offer geographic selects based upon the consumer's state or zip code. Since this information is part of the address itself, these selects can be offered with no additional investment by the list owner. Because they are so widely offered, we do not include these in our analyses.

than 24 months prior. While the decision to offer vintage names is clearly a type of recency select, we include the vintage variable to set a uniform standard of quality degradation across the lists.

List owners that offer dollar selects or recency selects also have to decide how many choices to offer. For instance, list owners can offer names of consumers who bought over $75 worth of items from the catalog at a premium from the price for names off the base list. The same manager could instead choose to offer two different dollar select options: names of those who bought over $50 worth of items at a low premium, or names of those who bought over $100 worth of items at a high premium.[9] Recency selects work very similarly: in addition to his or her base list, one list owner may choose to offer one recency select with names of consumers who made a purchase from the catalog within the last six months, while another owner may offer three selects; names of consumers who made a purchases in the last three months, the last six months or the last 12 months.

List owners can also engage in third-degree price discrimination. The most common form of third degree price discrimination involves offering a discount to fundraisers or not-for-profits. roughly 45% of catalog lists offer this type of discount. These fundraiser discounts can be substantial and often involve the additional perk of not having to pay an additional premium for any requested selects. The other type of third degree price discrimination we examine is whether the mailing list owners charge a premium to marketers from businesses that compete directly against the underlying catalog; approximately 10% of lists have such a surcharge.

When a marketer rents a list from a list owner, the list owner sends the names directly to a third party printshop/mailing house that processes the mailing. If the

[9] Of course, one of the cutoffs for the two groups could be the same as the cutoff for the one group.

mailer wishes to send out a second mailing to the same consumers then they must pay for the access to the mailing list twice. The use of the third party is one way to ensure that the mailers are not able to resell the mailing list. Additionally, list owners include a few fake addresses ("seeds") among the actual names, so they can confirm that their lists are being used only once and that mailings only include authorized materials. Preventing the resale of the access to the lists is what makes price discrimination possible.

The mailing list industry was not as technologically advanced in 1997 as some readers might anticipate. While the technology had advanced beyond the stage of storing data on physical cards, the 1997 technology primarily used magnetic tape to transfer data between the parties. Data files maintained by the list manager were often extracts of data used for the catalogs operations. To offer selects, these extracts needed to include the extra fields on which to separate the data. Thus, if a firm wanted to offer a gender select then the firm had to invest in extracting gender data from its main files. To offer very recent names the firm had to invest in technology to make rapid updating easy and efficient. The main point is that, counter to our intuition today, choosing to price discriminate did involve significant fixed-cost investments.[10] By 2002 these fixed costs had decreased, although the industry was still not near the forefront of technology. Note, though, that the marginal cost of price discriminating is zero once the fixed cost of price discriminating along a certain dimension has been made. That is, once the database has been adjusted to allow price discrimination along a given dimension there are no additional costs based on the number of times that particular field in the database is utilized.

The degree to which marginal costs are truly zero is underscored by the fact

[10]For lists maintained on paper cards, an owner wishing to discriminate had to keep three sets of names: a master list with all of the names, a list with all of the names of the men, and a list with all of the names of the women. Such a division would be required for any select that the mailing list offered.

that the mailer is charged for any additional costs besides the costs of the names themselves when purchasing names from a list owner. For example, this includes a fee for any media, such as magnetic tape, on which the names are delivered.

3.2.2 Data

This paper focuses on catalog-based response lists, which include the names of people who have either ordered from, or in some cases inquired about, a mail-order catalog. One reason we choose to study this industry is that this market is a byproduct of the list owner's primary business, namely selling merchandise through catalogs. That is, firms are not establishing new mail order catalogs for the purpose of renting a mailing list. As such, the firms' entry decisions, and by extension our competition measures, can be treated as exogenous in the analysis of the decision to price discriminate.

The data for this project consists of datacards for catalog-based consumer response list as of June 1997 and May 2002. The sample restrictions imply that the names on each list are consumers (rather than businesses) who have inquired about or purchased from a given catalog. The data include every datacard in the database maintained by Marketing Information Network (mIn), a company that supplies this directory to market participants looking to rent a list. Mailers, or their marketing agents, pay for a subscription to the mIn directory service and are then able to search the database for lists to rent.[11]

Each datacard includes the catalog name and the quantity of names available (in discrete categories) along with the price per thousand names. The datacard also lists the availability, name counts, and prices for all selects.

Tables 3.1 and 3.2 describe the data. In 1997, there were roughly 1,800 datacards

[11] One other firm, SRDS, offers a similar directory. However, only mIn offered an online database at the time of the first sample.

for lists distilled from mail-order catalogs. From this, we excluded international lists, as well as lists that were no longer adding new names. Also, some firms used multiple datacards to represent names from the same list. In these cases, we aggregated all datacards that we judged to be segments of the same base list into a single observation. This leaves a sample of 1,209 lists in 1997, and 1,405 lists in 2002. These values however, mask substantial entry and exit: of the original 1,200 lists available in the first period, roughly 500 exited by 2002. Most lists are relatively small, containing under 100,000 names, although a few have over 1 million names.

Tables 3.1 and 3.2 also show the fraction of lists offering the different selects in each year. Gender selects are offered by between just over half to two-thirds of the lists, depending on the sample year. Dollar selects are offered by about 40% of lists, while recency selects are offered by about 67% of lists. Multi-buyer selects are much less common: only about 15% of lists offer a multi-buyer select. The offering of vintage and inquirers only names both drop from about 43% of lists in 1997 to about 35% of lists in 2002. The lines labeled "Differential Rates" in these tables show the fraction of lists engaging in third-degree price discrimination. Approximately 45% of lists offered special reduced rates to fundraisers or not-for-profit organizations, while a much smaller number charge higher prices to firms that compete in the same underlying business.

Table 3.3 presents the correlations between the different price discrimination variables. In general, the correlations tend to be positive, suggesting that lists that price discriminate tend do so in a number of ways. However, the correlations are generally low, allowing us to treat each pricing decision as a separate test of the link between competition and price discrimination.

3.2.3 Measures of Competition

Our competition measures are derived from the 47 different categories into which mIn classifies lists.[12] Most of the lists are classified into one or two categories (see Figure 3.1) and a careful inspection of the data suggests that cases where the lists are classified in multiple categories are legitimate.

Using this classification, our basic approach to calculating competition measures is to add the number of lists that are classified in the same categories as the given list. However, this approach is complicated by the fact that lists often only partial overlap in their industry classifications. In these cases, we use measures where lists that partially overlap in their classifications count as providing some competition, but less than those lists that have exact matches. Note that this is justified not only in terms of the underlying characteristics of the list, but also in the institutional way that many of the marketers used to decide which mailing list to purchase: Using the mIn software, mailers can search by inputting industry codes and then choosing lists from the results of those queries.

We use three different measures of competition in order to ensure that the exact way that we calculate our competition measure is not driving our results. All three measures are based on the same principle: lists that have no overlapping classification codes are given a competitor weight of zero, lists that have exactly the same classification codes are given a weight of one, and lists that partially overlap are given a weight between zero and one. The competition measure is then the sum of these

[12] The categories used are Animals/Pets/Wildlife, Apparel, Areas Of Interest, Arts Cultural/Musical, Attendees, Beauty & Cosmetics, Boats/Boating, Books, Children, Children's Apparel, Children's Books/Pubs, Children's Merchandise, Collectibles, Computers, Diet & Fitness, Electronics, Environment, Fishing, Food/Kitchen Equipment, Furniture, Games/Contests/Puzzles, Gardening/Horticulture, General Merchandise, Gifts, GunsWeapons, Health, History, Hobbies Or Crafts, Home Decor/Accessories, Home Improvement, Hunting, Jewelry, Leisure/Recreation, Lotteries/Gambling, Mens Publications/Books, Motor Vehicles, Music, Photography, Record/Cassette/CD, Sexually Oriented, Sports, Sports Merchandise, Tools/Equipment, Travel, Video Tapes, Womens Publications/Books, Woodworking.

weights. The variation in our three competition measures lies in how they calculate the weight for partially-overlapping lists.[13]

Our main competition measure, CompMatch, is constructed by calculating pairwise the fraction of codes present for two lists that are common between them, and then summing this value for all pairs of lists. Specifically,

$$CompMatch_i = \sum_{\text{lists } j \neq i} \frac{\text{Number of codes listed by both } i \text{ and } j}{\text{Number of codes listed by } i \text{ or } j} \tag{1}$$

CompMatch has the advantage of being intuitive, symmetric and utilizing the information of non-matching codes from both lists.

We also examine whether we get similar results when we use two other measures of competition; CompAve and CompCos. CompAve is calculated as:

$$CompAve_i = \sum_{\text{lists } j \neq i} \frac{\text{Number of codes listed by both } i \text{ and } j}{\text{Number of codes listed by list } i} \tag{2}$$

CompAve is similar to CompMatch, except that the denominator includes only those codes on the list list for which competition is being calculated. This measure is a bit awkward because it is asymmetric and because it throws away some information about the degree of proximity of lists. However, it is the average number of competitors that will appear in any query that would include the featured list, so it has some intuitive appeal.

To calculate the last measure, we first create a vector of ones and zeros to indicate whether a particular list is classified as being in each industry. CompCos is then constructed by calculating the cosine of the angle formed between the code vector and a similar vector for each other list and then summing over all lists. The cosine between two lists with exactly the same industry codes is one while the cosine for

[13]These measures are related to distance metrics frequently used in cluster analysis involving binary variables. See Anderberg (1973) for a discussion of these metrics.

lists with no overlap is zero, and, because all vectors are non-negative, any partial overlap will lead to a cosine between zero and one. More formally,

$$CompCos_i = \sum_{\text{lists } j \neq i} \cos(i, j)$$
$$= \sum_{\text{lists } j \neq i} \frac{\text{Number of codes listed by both } i \text{ and } j}{\sqrt{\text{Number of codes listed by list } i * \text{Number of codes listed by list } j}} \quad (3)$$

The summary statistics for these competition variables appear in Table 3.1 and Table 3.2. A histogram of CompMatch appears in Figure 3.2 to give the reader a broader understanding of the distribution of competition. Table 3.4 then presents the correlations between these different measures. The correlations between these measures are high, largely because of the number of lists that are classified in only one or two industries.

CompMatch and the other competition measures attempt to capture the similarity between the different lists by accounting for the degree to which the lists are classified in the same way. However, one shortcoming of these competition measures, and of our data, is that we have limited ways to control for the degree of heterogeneity among the lists within a particular code. One consequence of not being able to fully capture product differentiation is that our measures of competition appear to be high. For example, while many lists have few competitors, the mean number of competitors for each list was near 90. In interpreting our main results, our assumption is that these measures are correlated enough, or even proportional, to the 'true' amount of competition.

However, to control for some of the unobserved heterogeneity, we also conduct an additional analysis using just lists with over 50,000 names. This is a reasonable approach to take if these lists form their own 'markets,' different from the smaller, more specialized lists. In these regressions, the primary competition measure is recalculated assuming that only the larger lists compete with each other, and restricting the regression sample to the larger lists as well. The subsample includes about 60% of the original sample. Here, the mean number of competitors drops to 48. As we report later, the main results generally become stronger when we do this.[14]

Finally, all of the results presented in this paper focus on the impact of the natural log of competition. We focus on the log of competition because, consistent with many theories of competition, we expect that the impact of each marginal competitor becomes smaller as the total number of competitors increases. That is, we expect that the differences between having 10 vs. 20 competitors is substantially larger than the difference between having 130 vs. 140 competitors. We have also confirmed that this functional form is reasonable by using other flexible forms, such as including linear and squared terms, which give similar curvature.

3.2.4 Other Variables

In addition to the competition measure, the estimation controls for the size of each mailing list. There are two reasons we include the size of the list in the regression. First, smaller lists may find it harder to recover any fixed costs that are necessary to engage in price discrimination because their revenues will generally be lower.[15] Second, there is an inherent tradeoff when offering selects: While offering a select can increase the total number of customers that rent the list and increase the price per name, some direct mailers who choose a select may have chosen to rent the entire base list if the select were not available. Generally, prices observed in the data dictate that revenues from selling an entire list are greater than revenues from selling

[14] We have also conducted the analysis further restricting the sample to only those lists with over 100,000 names without altering the results.

[15] These fixed costs are discussed earlier in section 3.2.

an entire select. Smaller lists will find that the probability of selling their full list are higher than they are for larger lists, where orders are constrained by the size of the marketer's budget or campaign. For both of these reasons, we hypothesize that price discrimination will increase with list size.

The focus of this study is on the relationship between market structure and the incentives to price discriminate. To control for the possibility that the decision to price discriminate depends on the size of demand for a mailing list instead of the the number of competitors, the empirical specifications include measures of market size. We do not observe direct quantity data, nor do we know how many mailers may be interested in a given list. Instead we proxy market size with the average total sales in the industries with the NAICS codes that best match the mIn categories. These data are collected from the Economic Census. When mailing lists classify themselves in multiple industries, we average over all of the mIn categories for which we were able to match NAICS codes. Because the industry size information is missing for some observations, the number of observations used in the estimation is reduced from 1,209 (1,405) to 1,094 (1,268) in 1997 (2002).[16]

3.3 Results

Our findings broadly demonstrate that mailing list owners in more competitive industries are more likely to price discriminate. We find that this is true for both second- and third-degree price discrimination. Further, among those mailing lists that choose to implement second-degree price discrimination, those in more competitive markets tend to offer menus with more options than those in less competitive markets.

[16] In prior versions of the paper, we also report results using the number of establishments or employees in the industry (using the same NAICS match) as alternate specifications. These other measures do not change the results.

3.3.1 Second-Degree Price Discrimination

We estimate the choice of whether to use each of the different types of price discrimination strategies (selects) as separate probit regressions.[17] We also run two OLS regressions where the dependent variables are the number of dollar selects and recency selects offered. Table 3.5 presents results from 1997, while Table 3.6 presents results from 2002. The coefficients on competition are positive across all specifications and across all years. All of the competition coefficients are also statistically significant at the 5% level, except for gender select and inquirers only availability.

The positive, statistically significant coefficients on competition demonstrate that mailing lists in markets with high levels of competition are more likely to exhibit second-degree price discrimination. The first several columns - those for gender selects, dollar selects, recency selects and multi-buyer selects - can be interpreted as examples of offering products of higher quality in order to price discriminate. The next two columns, those for vintage names and inquirers only, are examples of quality degradation - deliberately offering a degraded quality product in order to siphon off the low valuation buyers.

To gauge the approximate magnitude of the effects, the first line of each panel in Table 3.7 reports the increase in the probability of price discriminating that would be associated with moving from the 10th percentile of the competition measure to the 90th percentile, holding the other variables fixed at their respective means. The largest effect is for dollar selects, where the increase in competition is associated with a 26% (32%) increase in the probability of price discriminating in 1997 (2002). In the data, roughly 40% of lists offer this select, indicating that competition seems to have a substantial effect. Similarly, moving between these two levels of competition

[17] Estimating a regression where the number of types of price discrimination is the dependent variable or jointly estimating the probits as a multivariate system both yield similar results.

is associated with an 16% increase in the probability of offering vintage names, compared to the 36% of lists that offer the select in 1997. The magnitudes of the effects for recency and multi-buyer selects are smaller, although the 7.2% change in probability associated with the multi-buyer select may seem more significant given that only 16% of all lists offer a multi-buyer select.

List owners offering dollar and recency selects also need to decide how many different dollar amounts or time horizon cutoffs they should offer. Thus, in addition to running probit regressions on whether mailing list owners offer these selects, we also sum the number of dollar selects or recency selects offered among those list owners who price discriminate and regress these counts on our competition measure.[18] The results of these regressions are reported in columns 7 and 8 of Tables 3.5 and 3.6. The coefficients on competition are positive and significant, indicating that greater competition is correlated with a greater partition of the product space. The two columns for counts in Table 3.7 show the difference in the expected number of dollar and recency selects offered at the 10th and 90th percentiles of competition, evaluating all other variables at their respective means. The change of roughly .35 dollar select counts represents an increase of 12.5% relative to the mean of roughly 2.8 in the sample. The results for recency are quite similar.

The results also show that owners of large mailing lists are more likely to price discriminate than owners of small mailing lists. To see this note that, except in the case of inquirers, lists with over 50,000 names on them are always statistically more likely to price discriminate than those lists with less than 50,000 names. It is also true that lists with over 100,000 names are more likely to price discriminate than lists with between 50,000 and 100,000 names, although the statistical significance and

[18]Similar results are obtained when the observations where these selects are not offered are included in the regressions.

uniformity of this result is smaller. However, once lists are large enough - perhaps 200,000 names - it appears that additional names no longer factor into the decision to price discriminate. There is also evidence that larger lists offer menus with more choices to consumers. These results are consistent with the hypotheses advanced in Section 3.2.4 - that owners of small lists have a harder time recovering fixed costs of price discrimination, and that small lists may forgo selling their full list by offering selects.

3.3.2 Third-degree Price Discrimination

We examine the link between competition and third-degree price discrimination by considering two types of third-degree price discrimination observed in the data: fundraiser rates and competitor rates. As was the case for second-degree price discrimination, probit regressions reveal that greater competition is associated with a greater propensity to price discriminate, although the effect is stronger for the fundraising channel. The changes in the probability of offering a fundraiser rate corresponding to the difference between the 90th and 10th percentiles of the competition measures is 33% (29%) in 1997 (2002). This probability is only 4.2% (6.0%) for charging competitor rates, although only 9% (13%) of all lists have a competitor surcharge in 1997 (2002).

We also still find that larger lists are more likely to third degree price discriminate than smaller lists.

3.3.3 Alternate Specifications

Table 3.7 demonstrates that our results are robust to the precise specification that we use. As described above, this table reports the descriptive (not causal) differences in probabilities of price discriminating associated with the 90th percentile of competition compared to those associated with the 10th percentile.

As referenced in Section 3.2.3, one potential issue is the degree to which heterogeneity within industry codes is left uncaptured by our competition measures. As one possibility, small lists might be specialty lists that appeal to different direct mailers than large lists do. To examine this issue, we reran our analysis using only lists that have more than 50,000 names. The second line in Table 3.7 reports these results. Generally, both the magnitude and statistical significance of the results are increased. In 1997, the coefficient on competition in the inquirers-only probit becomes significant while the effect of competition in the competitor surcharge probit becomes insignificant; neither of these changes are observed in 2002, suggesting that these changes are probably random noise.

In a similar vein, the histograms of our competition measure presented in Figure 3.2 show a spike in competition at the high end of the distribution, which is due to the presence of many lists in the apparel industry. A skeptical reader might suspect that our results are mostly driven by the probability that mailing lists in the apparel industry choose to price discriminate. The third line in Table 3.7 reports results from a model that includes an indicator variable for whether the list is in the apparel industry. We find that the results are generally of a similar magnitude and significance, even controlling for this effect.

The next two lines show that the results are generally robust to the way that we measure competition. If we construct the competition measures using either CompAve or CompCos, we see that, in general, the results are similar in magnitude and significance to the CompMatch results.

Lastly, the final line in Table 3.7 presents the way that our results would change if we included fixed effects for the different list managers. One might hypothesize that the results presented above are the result of the fact that a few large managers who happen to be in more competitive industries tend to be more likely to price discriminate. One response would be to note that this would not invalidate the robustness of our results. It is possible that those lists in very competitive industries choose to go to large, sophisticated managers in order to compete more effectively. In spite of this argument, we include indicator variables for each of the managers[19] and find that the results are, for the most part, qualitatively similar, underscoring the strength of our results.

The second panel of Table 3.7 reports the results from the 2002 data. Taken together, along with the fairly high levels of entry and exit, the two panels of Table 3.7 demonstrate the robustness of our results to the precise specification of the estimated model.

3.4 Conclusion

Theoretical ambiguity as to whether more-intense competition should lead to more or less price discrimination leaves the net impact as an empirical question. Mailing lists provide a good context in which to study this question because mailing lists are zero-marginal cost goods, meaning that differences in prices must be the result of demand, not cost. We find that greater competition is associated with more second- and third-degree price discrimination and that firms that implement second-degree price discrimination in more-competitive industries offer consumers menus with more choices.

There are at least two reasons why competition might lead to increased price discrimination. First, the increased probability of losing customers to competitors

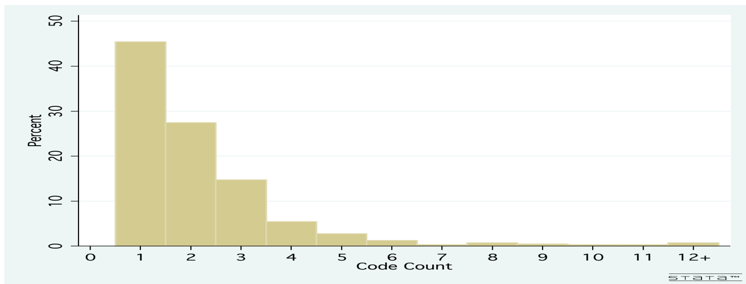
[19] Because indicator variables for managers who have only one list would perfectly predict whether the client list price discriminates, we create an indicator variable for small managers, and assign this indicator for all managers that manage one or two lists.

may trigger a prisoner's dilemma where firms pay the sunk costs required for price discrimination. Second, increased competition can lead firms to price discriminate in order to extract surplus from those consumers who care a lot about cross-firm product differentiation while retaining those consumers who view products from different firms as close substitutes.

While we cannot test which of the theories leads to our conclusion, it is interesting to note that our results are consistent with this last hypothesis. For example, it is likely that the marketers who gain the most value from a multi-buyer select are those marketers who are promoting products that are similar to those offered in the catalog from which the mailing list was derived. These marketers are also the marketers who are most sensitive to product differentiation: The value they obtain from purchasing names from a list derived from a catalog selling very similar products compared to a list derived from a more distant product is high, while those marketers who are selling products that are only somewhat related to the underlying product do not care as strongly which list they purchase and are unlikely to pay for a multi-buyer select. The argument for dollar selects is the same. The logic would apply to recency and vintage selects to the extent that people's purchasing patterns change more quickly than their underlying interests and that it is possible to target consumers with specific interests through a broader set of lists than one could use to target purchasing patterns. For third degree price discrimination, fundraisers probably see the various mailing lists as relative commodities, while marketers care about the catalog from which the mailing list was derived; Marketers representing direct competitors are the most sensitive to product differentiation between lists. In contrast, it is harder to fit this reasoning on the gender and inquirers only selects - the two selects where our results are statistically insignificant.

There are reasons to believe that these results generalize outside of the mailing list industry. In particular, many observed practices conform to the idea that competition increases price discrimination which segments consumers by their sensitivity to product differentiation. For example, in the airline industry the gap between unrestricted and restricted fares increases with competition (Stavins (2001)), consistent with business consumers who buy unrestricted fares generally having the lowest willingness to take another airline due to their desire for direct flights at their optimal time and/or from benefits of a rewards program. In the newspaper industry, greater poaching is observed in more-competitive markets (Asplund et al. (2002)), and the lower subscription rates offered to consumers in geographic areas better covered by another paper picks off those consumers who do not care as much about the locality of their paper. Finally, it is possible that the merchants who buy large yellow page advertisements in the market studied by Busse and Rysman (2005) are the ones most likely to reallocate their advertising strategy (or size) when competitors offer them more outlets in which to advertise. Our results, taken together with these other empirical studies, suggest that the connection between competition and increased price discrimination is a result that applies broadly.

Figure 3.1: Distribution of Number of Codes Describing Lists - 1997, 2002



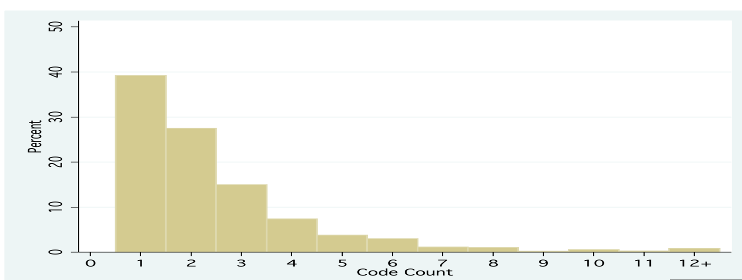


Figure 3.2: Distribution of Competition Measure - CompMatch - 1997, 2002

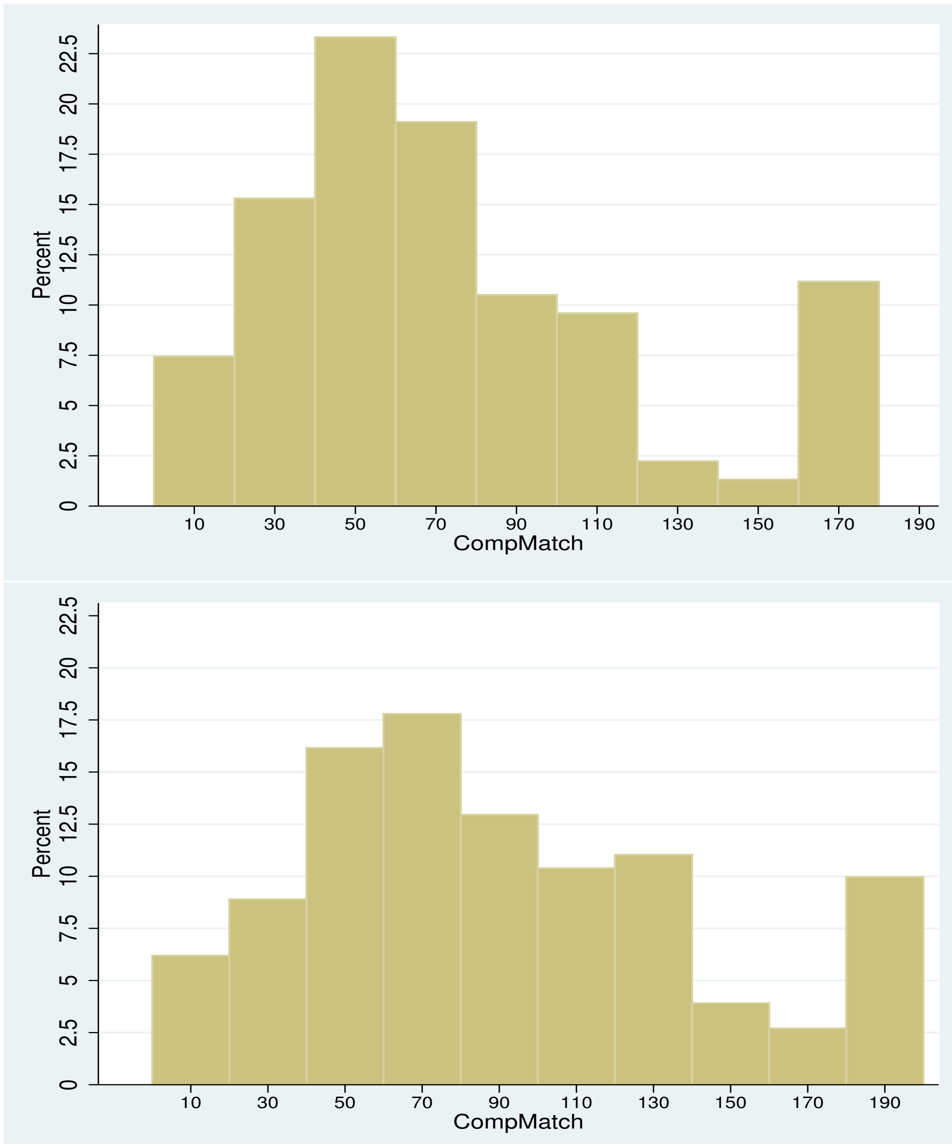


Table 3.1: Summary Statistics 1997

Variable	N	Mean	Std. Dev.	Min	Max
List Size					
0-49,999 Names	1209	0.40	0.49	0	1
50,000-99,999 Names	1209	0.23	0.42	0	1
100,000-199,999 Names	1209	0.15	0.36	0	1
200,000-299,999 Names	1209	0.07	0.25	0	1
300,000-399,999 Names	1209	0.04	0.19	0	1
400,000-499,999 Names	1209	0.03	0.17	0	1
500,000-999,999 Names	1209	0.05	0.21	0	1
1,000,000+ Names	1209	0.04	0.20	0	1
Selects Available					
Gender Select Available	1209	0.55	0.50	0	1
Dollar Select Available	1209	0.38	0.49	0	1
Recency Select Available	1209	0.68	0.47	0	1
Multi-Buyers Available	1209	0.15	0.36	0	1
Vintage Names Available	1209	0.43	0.49	0	1
Inquirers Available	1209	0.43	0.49	0	1
Select Counts					
Dollar Select Count	461	2.83	1.19	1	7
Recency Select Count	824	2.35	1.11	1	7
Differential Rates					
Fundraiser Rate Available	1209	0.43	0.50	0	1
Competitor Rate Available	1209	0.09	0.29	0	1
CompMatch	1209	74.80	44.86	2.21	167.79
CompAve	1209	120.12	71.83	4	281
CompCos	1209	108.49	64.25	3.12	257.10
Control Variables					
Apparel Indicator	1209	0.23	0.42	0	1
Mkt Size: Dollar ($bil)	1094	63.26	88.80	2.25	560.30

Table 3.2: Summary Statistics 2002

Variable	N	Mean	Std. Dev.	Min	Max
List Size					
0-49,999 Names	1405	0.37	0.48	0	1
50,000-99,999 Names	1405	0.20	0.40	0	1
100,000-199,999 Names	1405	0.17	0.37	0	1
200,000-299,999 Names	1405	0.08	0.27	0	1
300,000-399,999 Names	1405	0.04	0.20	0	1
400,000-499,999 Names	1405	0.03	0.16	0	1
500,000-999,999 Names	1405	0.05	0.22	0	1
1,000,000+ Names	1405	0.05	0.23	0	1
Selects Available					
Gender Select Available	1405	0.67	0.47	0	1
Dollar Select Available	1405	0.40	0.49	0	1
Recency Select Available	1405	0.66	0.47	0	1
Multi-Buyers Available	1405	0.16	0.37	0	1
Vintage Names Available	1405	0.36	0.48	0	1
Inquirers Available	1405	0.35	0.48	0	1
Select Counts					
Dollar Select Count	566	2.89	1.18	1	8
Recency Select Count	933	2.41	1.20	1	12
Differential Rates					
Fundraiser Rate Available	1405	0.47	0.50	0	1
Competitor Rate Available	1405	0.13	0.34	0	1
CompMatch	1405	90.26	50.55	1.38	191.01
CompAve	1405	155.34	86.07	4	358
CompCos	1405	138.85	77.69	2.01	340.24
Control Variables					
Apparel Indicator	1405	0.26	0.44	0	1
Mkt Size: Dollar ($bil)	1268	91.50	128.	3.11	725.60

Table 3.3: Correlation Among Price Discrimination Variables

	Dollar Select Available	*Gender Select Available*	*Recency Select Available*	*Multi-Buyers Available*	*Vintage Names Available*	*Inquirers Available*	*Fundraiser Rate Available*	*Competitor Rate Available*
				1997				
Dollar Select	1.00	0.19	0.50	0.36	0.24	0.05	0.59	0.09
Gender Select	0.19	1.00	0.14	0.15	0.06	-0.00	0.15	0.04
Recency Select	0.50	0.14	1.00	0.26	0.36	0.10	0.38	0.12
Multi-Buyers	0.36	0.15	0.26	1.00	0.10	0.14	0.29	0.06
Vintage Names	0.24	0.06	0.36	0.10	1.00	0.09	0.23	0.07
Inquirers	0.05	-0.00	0.10	0.14	0.09	1.00	0.03	0.02
Fundraiser Rate	0.59	0.15	0.38	0.29	0.23	0.03	1.00	0.07
Competitor Rate	0.09	0.04	0.12	0.06	0.07	0.02	0.07	1.00
				2002				
Dollar Select	1.00	0.16	0.50	0.31	0.24	0.05	0.55	0.15
Gender Select	0.16	1.00	0.12	0.11	-0.01	-0.02	0.15	-0.01
Recency Select	0.50	0.12	1.00	0.20	0.42	0.10	0.40	0.14
Multi-Buyers	0.31	0.11	0.20	1.00	0.08	0.12	0.24	0.03
Vintage Names	0.24	-0.01	0.42	0.08	1.00	0.09	0.25	0.16
Inquirers	0.05	-0.02	0.10	0.12	0.09	1.00	0.06	0.08
Fundraiser Rate	0.55	0.15	0.40	0.24	0.25	0.06	1.00	0.22
Competitor Rate	0.15	-0.01	0.14	0.03	0.16	0.08	0.22	1.00

Table 3.4: Correlation Among Competition Measures

	1997		
	CompMatch	*CompAve*	*CompCos*
CompMatch	1.00	0.95	0.94
CompAve		1.00	0.85
CompCos			1.00
	2002		
CompMatch	1.00	0.93	0.95
CompAve		1.00	0.80
CompCos			1.00

Table 3.5: Main Results - 1997

	Dollar Select Available	Gender Select Available	Recency Select Available	Multi-Buyers Available	Vintage Names Available	Inquirers Available	Dollar Select Count	Recency Select Count	Fundraiser Rate Available	Competitor Rate Available
	Probit	Probit	Probit	Probit	Probit	Probit	OLS	OLS	Probit	Probit
Constant	$\mathbf{-4.300}^{***}$	$\mathbf{-2.466}^{***}$	$\mathbf{-1.241}^{*}$	$\mathbf{-2.609}^{***}$	$\mathbf{-1.536}^{**}$	0.573	0.079	$\mathbf{1.137}^{*}$	$\mathbf{-3.085}^{***}$	$\mathbf{-2.620}^{***}$
	(0.702)	(0.640)	(0.701)	(0.824)	(0.636)	(0.631)	(0.994)	(0.613)	(0.668)	(0.977)
ln(*CompMatch*)	$\mathbf{0.398}^{***}$	0.068	$\mathbf{0.143}^{**}$	$\mathbf{0.184}^{**}$	$\mathbf{0.208}^{***}$	0.060	$\mathbf{0.147}^{*}$	$\mathbf{0.217}^{***}$	$\mathbf{0.503}^{***}$	$\mathbf{0.216}^{**}$
	(0.062)	(0.056)	(0.060)	(0.074)	(0.055)	(0.055)	(0.087)	(0.054)	(0.061)	(0.090)
Size: 50-99	$\mathbf{0.678}^{***}$	$\mathbf{0.525}^{***}$	$\mathbf{0.673}^{***}$	$\mathbf{0.546}^{***}$	$\mathbf{0.399}^{***}$	0.078	$\mathbf{0.407}^{**}$	$\mathbf{0.588}^{***}$	$\mathbf{0.351}^{***}$	0.168
	(0.114)	(0.103)	(0.106)	(0.150)	(0.103)	(0.102)	(0.190)	(0.101)	(0.107)	(0.174)
Size: 100-199	$\mathbf{1.168}^{***}$	$\mathbf{0.544}^{***}$	$\mathbf{1.209}^{***}$	$\mathbf{0.621}^{***}$	$\mathbf{0.345}^{***}$	0.055	$\mathbf{0.569}^{***}$	$\mathbf{0.658}^{***}$	$\mathbf{0.692}^{***}$	$\mathbf{0.473}^{***}$
	(0.123)	(0.115)	(0.138)	(0.159)	(0.115)	(0.114)	(0.183)	(0.104)	(0.118)	(0.171)
Size: 200-299	$\mathbf{1.349}^{***}$	$\mathbf{0.627}^{***}$	$\mathbf{1.086}^{***}$	$\mathbf{0.980}^{***}$	$\mathbf{0.504}^{***}$	$\mathbf{0.308}^{**}$	$\mathbf{0.566}^{***}$	$\mathbf{1.105}^{***}$	$\mathbf{0.750}^{***}$	$\mathbf{0.600}^{***}$
	(0.165)	(0.158)	(0.183)	(0.188)	(0.155)	(0.154)	(0.217)	(0.138)	(0.159)	(0.213)
Size: 300-399	$\mathbf{1.776}^{***}$	$\mathbf{0.731}^{***}$	$\mathbf{2.061}^{***}$	$\mathbf{1.297}^{***}$	$\mathbf{0.484}^{**}$	$\mathbf{0.367}^{*}$	$\mathbf{1.060}^{***}$	$\mathbf{1.294}^{***}$	$\mathbf{0.991}^{***}$	$\mathbf{0.986}^{***}$
	(0.231)	(0.215)	(0.437)	(0.229)	(0.209)	(0.206)	(0.250)	(0.171)	(0.215)	(0.247)
Size: 400-499	$\mathbf{1.802}^{***}$	$\mathbf{0.928}^{***}$	$\mathbf{1.521}^{***}$	$\mathbf{1.938}^{***}$	$\mathbf{0.501}^{**}$	0.083	$\mathbf{0.858}^{***}$	$\mathbf{1.294}^{***}$	$\mathbf{1.034}^{***}$	$\mathbf{0.694}^{**}$
	(0.281)	(0.260)	(0.360)	(0.255)	(0.238)	(0.237)	(0.277)	(0.196)	(0.257)	(0.298)
Size: 500-999	$\mathbf{1.687}^{***}$	$\mathbf{0.859}^{***}$	$\mathbf{1.251}^{***}$	$\mathbf{1.541}^{***}$	$\mathbf{0.870}^{***}$	$\mathbf{0.361}^{**}$	$\mathbf{0.724}^{***}$	$\mathbf{1.505}^{***}$	$\mathbf{1.234}^{***}$	$\mathbf{0.808}^{***}$
	(0.205)	(0.197)	(0.235)	(0.205)	(0.190)	(0.184)	(0.234)	(0.159)	(0.203)	(0.236)
Size: 1,000+	$\mathbf{1.680}^{***}$	$\mathbf{0.755}^{***}$	$\mathbf{1.542}^{***}$	$\mathbf{1.858}^{***}$	$\mathbf{0.594}^{***}$	$\mathbf{0.600}^{***}$	$\mathbf{0.877}^{***}$	$\mathbf{1.864}^{***}$	$\mathbf{1.294}^{***}$	$\mathbf{0.774}^{***}$
	(0.224)	(0.206)	(0.296)	(0.218)	(0.198)	(0.198)	(0.242)	(0.164)	(0.223)	(0.247)
ln(Mkt Size: Dollar)	$\mathbf{0.093}^{**}$	$\mathbf{0.112}^{***}$	0.035	0.008	0.013	$\mathbf{-0.063}^{*}$	0.090	-0.020	0.023	-0.003
	(0.041)	(0.038)	(0.042)	(0.049)	(0.038)	(0.038)	(0.060)	(0.038)	(0.040)	(0.060)
Correctly Predicted	0.736	0.615	0.694	0.863	0.617	0.598			0.674	0.908
R^2							0.086	0.264		
N	1094	1094	1094	1094	1094	1094	428	760	1094	1094

Table 3.6: Main Results - 2002

	Dollar Select Available	Gender Select Available	Recency Select Available	Multi-Buyers Available	Vintage Names Available	Inquirers Available	Dollar Select Count	Recency Select Count	Fundraiser Rate Available	Competitor Rate Available
	Probit	Probit	Probit	Probit	Probit	Probit	OLS	OLS	Probit	Probit
Constant	**−3.227*****	**−1.261****	**−2.251*****	**−2.945*****	**−1.536*****	-0.772	0.655	-0.231	**−2.192*****	**−2.098*****
	(0.613)	(0.591)	(0.598)	(0.739)	(0.586)	(0.582)	(0.861)	(0.660)	(0.589)	(0.771)
ln($CompMatch$)	**0.535*****	0.010	**0.233*****	**0.220*****	**0.190*****	0.034	0.140	**0.207*****	**0.458*****	**0.245*****
	(0.064)	(0.056)	(0.058)	(0.074)	(0.056)	(0.056)	(0.091)	(0.064)	(0.059)	(0.077)
Size: 50-99	**0.584*****	**0.284*****	**0.580*****	**0.471*****	**0.175***	0.002	**0.341****	**0.477*****	**0.274*****	0.135
	(0.104)	(0.101)	(0.102)	(0.143)	(0.101)	(0.102)	(0.155)	(0.112)	(0.100)	(0.138)
Size: 100-199	**0.662*****	**0.410*****	**0.732*****	**0.770*****	0.122	0.095	**0.604*****	**0.606*****	**0.463*****	**0.304****
	(0.110)	(0.109)	(0.111)	(0.140)	(0.107)	(0.106)	(0.156)	(0.115)	(0.106)	(0.138)
Size: 200-299	**1.093*****	**0.750*****	**0.850*****	**1.176*****	**0.264***	**0.251***	**0.831*****	**1.051*****	**0.890*****	**0.718*****
	(0.149)	(0.161)	(0.158)	(0.165)	(0.142)	(0.142)	(0.179)	(0.147)	(0.150)	(0.163)
Size: 300-399	**0.973*****	**0.681*****	**1.163*****	**1.224*****	0.028	0.010	**0.469****	**0.914*****	**0.805*****	**0.516****
	(0.181)	(0.200)	(0.223)	(0.198)	(0.182)	(0.181)	(0.221)	(0.173)	(0.184)	(0.209)
Size: 400-499	**1.037*****	0.304	**0.859*****	**1.056*****	0.225	0.302	**0.915*****	**1.028*****	**1.056*****	**0.551****
	(0.236)	(0.236)	(0.261)	(0.250)	(0.229)	(0.225)	(0.266)	(0.224)	(0.250)	(0.262)
Size: 500-999	**1.046*****	**0.710*****	**0.813*****	**1.195*****	0.043	0.167	**0.682*****	**1.242*****	**0.779*****	0.320
	(0.174)	(0.189)	(0.187)	(0.188)	(0.171)	(0.168)	(0.203)	(0.170)	(0.173)	(0.208)
Size: 1,000+	**0.850*****	**0.458*****	**0.803*****	**1.553*****	**0.302***	**0.584*****	**0.782*****	**1.273*****	**0.332****	0.311
	(0.166)	(0.171)	(0.181)	(0.179)	(0.161)	(0.160)	(0.205)	(0.165)	(0.162)	(0.201)
ln(Mkt Size: Dollar)	0.008	**0.080****	**0.070****	0.019	0.012	0.009	0.062	**0.067***	-0.011	-0.022
	(0.035)	(0.034)	(0.034)	(0.042)	(0.033)	(0.033)	(0.048)	(0.037)	(0.034)	(0.044)
Correctly Predicted	0.703	0.649	0.654	0.844	0.643	0.656			0.648	0.868
R^2							0.082	0.163		
N	1268	1268	1268	1268	1268	1268	527	847	1268	1268

Table 3.7: Alternate Specifications

	Dollar Select Available	Gender Select Available	Recency Select Available	Multi-Buyers Available	Vintage Names Available	Inquirers Available	Dollar Select Count	Recency Select Count	Fundraiser Rate Available	Competitor Rate Available
	Probit	Probit	Probit	Probit	Probit	Probit	OLS	OLS	Probit	Probit
					1997					
Base	**0.281*****	0.051	**0.091****	**0.071****	**0.156*****	0.045	**0.283***	**0.417*****	**0.364*****	**0.055****
Larger Lists	**0.382*****	0.009	**0.138*****	**0.134*****	**0.223*****	**0.107****	0.265	**0.498*****	**0.426*****	0.049
Apparel Controls	**0.206*****	**0.087***	0.019	0.049	**0.085***	0.033	0.266	**0.282****	**0.289*****	0.045
CompAve	**0.272*****	0.026	**0.086****	**0.055***	**0.149*****	0.022	**0.367****	**0.382*****	**0.383*****	**0.046****
CompCos	**0.262*****	**0.063***	**0.077****	**0.072*****	**0.159*****	0.029	**0.346****	**0.368*****	**0.336*****	**0.042****
Manager Indicators	**0.195*****	-0.007	0.026	**0.055****	**0.113****	0.019	0.197	**0.409*****	**0.288*****	**0.039****
					2002					
Base	**0.335*****	0.006	**0.140*****	**0.079*****	**0.118*****	0.021	0.236	**0.349*****	**0.299*****	**0.078*****
Larger Lists	**0.423*****	0.001	**0.192*****	**0.096****	**0.214*****	0.056	**.351***	**0.579*****	**0.390*****	**0.137*****
Apparel Controls	**0.318*****	0.061	**0.085****	0.040	0.015	-0.034	0.247	0.185	**0.238*****	0.035
CompAve	**0.294*****	-0.020	**0.123*****	**0.064****	**0.085****	-0.021	0.208	**0.299*****	**0.307*****	**0.073*****
CompCos	**0.316*****	0.039	**0.126*****	**0.085*****	**0.130*****	0.030	**0.296****	**0.424*****	**0.287*****	**0.060*****
Manager Indicators	**0.198*****	-0.020	**0.080****	**0.071*****	**0.094****	0.048	-0.030	**0.220***	**0.188*****	**0.072*****

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CHAPTER IV

Conclusion

This thesis demonstrates that two seemingly disparate questions, why different retailers offer different versions of a product, and how competition distorts the price schedule of a multi-version product, are in fact related to one another.

Chapter II developed a theoretical model suggesting that a trade-off between new products and different sizes of existing products only occurs if either consumers who prefer smaller sizes also prefer a particular product characteristic, or if shelving space is scarce.

Using data on a large supermarket chain, I employed a difference-in-differences strategy to investigate this model. I found that the introduction of new products typically causes the price gap to drop by 6%, This evidence supports the notion that firms with market power exchange discrimination for differentiation.

Chapter III examined issues similar to those in chapter II but in a multi-firm setting. This difference lead my co-authors and I to examine the market for mailing lists, where numerous list owners selling similar lists engage in both 2nd and 3rd degree price discrimination. One of the great advantages of this market is that the marginal cost of selling an additional select is zero, enabling us to distinguish price discrimination from differences in list costs, as well as to focus on the decision to price discriminate rather than a product's price schedule. We find that greater competition is associated with more second- and third-degree price discrimination and that firms that implement second-degree price discrimination in more-competitive industries offer consumers menus with more choices.

The results from these chapters appear to contradict one another. Chapter II indicates that the introduction of a close substitute will adversely affect a firm's ability to price discriminate. Chapter III, however, suggests the opposite; the introduction of a close substitute actually promotes price discrimination.

One explanation for this discrepancy is theoretical. In the competitive case, competition can trigger a prisoner's dilemma where each list pays the sunk costs required for price discrimination, but where all lists would be better off if no lists price discriminated Such a situation could arise if consumers obtained similar value from each of the products offered by a given firm. In this case, a firm without much competition has low incentives to pay the fixed costs of offering more choices to consumers since any new products simply cannibalize existing sales. However, when there is more competition, firms now have to focus on attracting consumers from competitors rather than focus on cannibalization.

A second explanation is data-related. Roughly speaking, the competitive measures employed in chapter III group mailing lists by industry. If these industry codes are too broad, then lists that are not close substitutes will be grouped together. If it is also the case that these lists do not have close substitutes, then we may obtain chapter III's result. This problem is less likely to be true for chapter II, as this chapter attempts to control for the presence of close substitutes using estimates from a discrete choice demand model.