Beyond Plain Vanilla: Modeling Joint Product Assortment and Pricing Decisions[¤]

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Abstract

This paper investigates empirically the product assortment strategies of oligopolistic ¯rms. We develop a framework that integrates product choice and price competition in a di®erentiated product market. The present model signi¯cantly improves upon the reduced-form pro¯t functions typically used in the entry and location choice literature, because the variable pro¯ts that enter the product-choice decision are derived from a structural model of demand and price competition. Given the heterogeneity in consumers' product valuations and responses to price changes, this is a critical element in the analysis of product assortment decisions. Relative to the literature on structural demand models, our results show that incorporating endogenous product choice is essential for policy simulations and may entail very di®erent conclusions from settings where product assortment choices are held ¯xed.

Keywords: product assortment decisions, multi-product ¯rms, discrete games

JEL Classi¯cation: L0, L1, L2, L8, M3

1 Introduction

Decisions about product assortments and prices are among the most fundamental choices ¯rms make. When selecting which products to o®er, a ¯rm in a competitive environment has to weigh the bene¯ts of a \popular" product space location against the potential downside of ¯ercer price competition. Ever since Hotelling's (1929) seminal paper, this fundamental tradeo® has been central to the literature. Deciding how to weigh demand against competitive considerations also remains a primary concern in applied contexts, with managers grappling over pricing and product assortment decisions.

The tradeo® between demand and strategic considerations is also at the heart of the empirical market entry literature (Seim 2006, Mazzeo 2002, Bresnahan & Reiss 1991, Bresnahan & Reiss 1987). This literature relies solely on information contained in discrete ¯rm decisions to infer bounds on pro¯tability. For example, the fact that a ¯rm operates in a particular market allows the inference that it is more pro¯table to operate in that location than to exit. The coarseness of these discrete data make it di±cult to base the pro¯t function on all but the simplest of demand structures, ones which generally do not represent product-market competition in oligopolistic industries with di®erentiated products well. As a result, the majority of the literature focuses on relatively homogeneous competitors, such as single-outlet retail stores in well-delimited, small markets. For frequently purchased products that di®er in attributes, quality, and brand value, the interplay between consumer preferences for product attributes and their price sensitivities is central to the product o®ering decision. Detailed modeling of demand and price competition is therefore of key importance in empirically assessing the determinants of product choices.

In this paper we develop an integrated empirical framework to investigate how ¯rms make product-choice decisions in di®erentiated products industries. In contrast to the extant empirical entry literature, we model explicitly product market competition between the products that ¯rms choose to o®er. The resulting structural pro¯t function allows us to separate the role of consumer preferences for products' attributes from marginal and ¯xed cost considerations for product introductions. We start with a discrete-choice demand model for di®erentiated products and from it develop an equilibrium model of joint product assortment and pricing decisions. The availability of richer data, in particular data on prices and quantities, allows us to better separate the strategic considerations in product assortment decisions from market heterogeneity that drives consumer demand and marginal costs.

We demonstrate in a series of counterfactual experiments how changes in demand or market structure a®ect equilibrium product assortments and prices. Considering product choices as strategic variables to the ¯rm when conducting policy analyses yields di®erent predictions than a simpler model that holds these ¯xed. We show, for example, that a reduction in the number of competitors due to a merger may be pro¯table for the merging ¯rm, while at the same time bene¯ting consumers in the form of higher product variety. To the extent that consumer surplus gains from product variety outweigh losses from higher prices in the more concentrated market, we illustrate that a merger may be unambiguously welfare enhancing. This prediction critically depends on the ability of ¯rms to respond in their assortment choices to the new market structure: With ¯xed assoortment choices consumers always lose from the merger due to higher prices.[1]

The existing literature has made considerable progress in characterizing competition among heterogeneous ¯rms by focusing on component parts of the product assortment decisions with separate streams of research. Structural demand models generate consistent estimates of price elasticities given the products that ¯rms have chosen to o®er, but they assume that these products and their characteristics are exon explaining entry and location decisions in situations where prices are not a choice variable of the ¯rm or use a reduced-form pro¯t function that does not explicitly incorporate the prices and quantities of the products o®ered. Firms' product-space locations and those of their competitors are the sole arguments of the ¯rms' objective function, thereby also limiting the scope of counterfactual exercises one can conduct using the estimated parameters. Without an explicit model of demand and post-entry product market competition, for example, we cannot make inferences about equilibrium prices after a product portfolio change, e.g., due to a merger. An early attempt to tackle this issue is Reiss & Spiller (1989), albeit in the context of symmetric ¯rms o®ering one of two products. Thomadsen (2007) uses estimated demand systems to conduct counterfactual analyses of location competition between single-outlet retailers. His work does not attempt to directly exploit the information entailed in for what to stock.

We model the possible o®erings in the \vanilla" subcategory, which is by far the most frequently purchased °avor, accounting for more than one quarter of all sales. Interestingly, in recent years there has been a number of new product introductions in this space - Breyers and Dreyers now o®er up to six varieties of vanilla. The size and evolution of the product category suggests that choices among vanillas are important in their own right, while also being representative of °avor o®ering decisions across the entire product assortment for these brands.

We consider a two-stage setup where ¯rms initially make their assortment decisions in a discrete game that draws on their variable pro¯ts derived in the subsequent stage of price competition. In our set-up, ¯rms have at their disposal a set of pre-

The remainder of this paper is organized as follows. In Section 2 we develop the modeling framework. Section 3 describes the ice cream market and the data we use for the empirical analysis. We outline our estimation approach in Section 4 and then discuss the estimation results in Section 5. The proposed modeling framework along with the estimated parameters allow us to conduct various policy experiments, which are presented in Section 6. Section 7 concludes with directions for future research.

2 Model

A total of $b = 1, \ldots, B$ ¯rms (brands)[4] decide which °avors to o®er in a given market and how to price them given their expectation of their competitors' o®erings, demand, and a ¯xed cost of o®ering each subset of °avors.

In the ¯rst stage, the ¯rms decide which °avors to o®er. Each ¯rm starts with a predetermined set of potential °avors to o®er and selects the optimal subset of °avors among this potential set. In the second stage, ¯rms observe each others' °avor choices. Conditional on their own and their competitors' choice of o®erings, ¯rms choose prices.

Clearly, ¯rms do not revise o®erings for all potential °avors in each period and market. There are certain °avors that a brand always o®ers. We call them staples. The assortment decisions being made concern only what we refer to as the optional °avors. The °avor choice model can be thus thought of applying to optional °avors of a brand that are not o®ered in all of the markets, as opposed to the staple °avors of a brand.[5] While we abstract from the product o®ering decision for staple °avors, our model takes into account the demand for staples in determining the price for all °avors in the market.

More formally, brand b has °avors $f = 1, 2, \ldots, O_b, O_b + 1, O_b + 2, \ldots, F_b$ at its disposal. The optional °avors are $1, \ldots, O_b$; °avors $O_b + 1, \ldots, F_b$ are the staples that the ¯rm always o®ers. Note that the optional and staple °avors may di®er from brand to brand. De¯ne the vector $d_{bt} = (d_{b1t}, \ldots, d_{bO_bt}) \in \{0, 1\}^{O_b}$, where d_{bft} indicates whether optional °avor f is o®ered by competitor b in market t.

[4] In the remainder of the paper we use ¯rms and brands interchangeably.

[5] The loss of information is not severe because all we can learn from the fact that a brand always o®ers a particular °avor is that the cost of o®ering that °avor is smaller than the lowest incremental variable pro¯t across periods from o®ering it, which would only yield an upper bound on such costs.

2.1 Stage 2

In the second stage, we solve for equilibrium prices for every possible combination of °avor choices. These prices then °ow back into the ¯rst stage to determine pro¯ts for each of the °avors that a ¯rm is considering.

Consumer demand. We assume a discrete choice model of demand. Let U_{bfkt} denote consumer k's utility for brand b's °avor f

istics presents a classic selection problem (Heckman 1978) because firms only offer products with anticipated high demand. Modeling firms' product assortment choice explicitly as we do is a potential way to correct for this selection bias, but it requires recovering the full distribution of the unobservable characteristics. While we can infer market/time-specific unobservable attributes associated with product assortment that have been chosen, inferring the value of the unobservables for non-offered products is infeasible without imposing additional (strong) assumptions. For example, if we assumed that firms only observe the demand shocks at the time of their pricing, but not at the time of their assortment decision, then firms would need to form expectations over them in choosing offerings. However, as will become clearer when we present the supply model below, a flavor's variable profit is a highly nonlinear function of the unobservables, so taking this expectation is a nontrivial exercise. In particular, we would need to make some distributional assumption for the unobservables, thus implying that we know the distribution of the equilibrium prices (see Berry (1994) for an explanation of why this type of assumption is inconsistent with the equilibrium model). Our solution to this problem is pragmatic: We assume that in our empirical setting the brand-flavor-specific constants in the demand system along with the market characteristics and time effects capture most of the unobserved determinants of brand-flavor shares across markets.

Firm profits. For a set of flavors determined in the first stage, firm b chooses prices to maximize expected profit. Firms are assumed to compete in Bertrand-Nash fashion, given their cost structures.

Firm b incurs a marginal cost of c_{bt} for each unit offered in market t. The marginal costs of offering a flavor include costs for ingredients such as milk, cream, sugar, and flavorings and costs of packaging, labeling, and distributing the product. We specify them as $c_{bt} = \sum_k w_{bkt}\gamma + \eta_{bt}$, where w_{bt} are brand-specific cost shifters k and η_{bt} is a brand-specific component of marginal cost.[6] We assume that firms observe each other's marginal costs when they choose prices, i.e., marginal costs are public information.

We follow the literature in allowing part of the marginal costs to be unobservable to the researcher (Berry et al. 1995). Similar to the demand-side problem of account-

[6]While our model readily accommodates cost shifters that are brand-flavor specific, our application to ice cream does not require this additional generality, see Section 4.1 for details.

ing for unobserved product characteristics for absent °avors, we have to confront the problem that we do not observe the value of the unobservable marginal cost components for a brand-°avor combination that is not o®ered. We solve this problem by assuming that the unobservable component of marginal cost varies by time and brand but not by °avor. Assuming that ¯rms set their prices optimally (conditional on the chosen assortment), we can then recover the value of this unobservable from the pricing ¯rst-order conditions and use it to estimate the ¯rm's marginal cost of °avors that it ultimately does not include in its assortment.

In addition, we assume ¯rm b has a ¯xed cost to o®er °avor f in each market t, $^{o}_{bft}$, distributed according to probability distribution function G_{bf} that di®ers across brands and °avors. The ¯xed costs of o®ering a °avor includes the operating costs of producing the °avor (foregone economies of scale due to smaller batches, cost of cleaning machines, labeling, etc.), the distribution costs of getting the °avor to customers (such as additional inventory and stocking costs that likely increase in the number of °avors o®ered), advertising costs associated with promoting the °avor (which may is that we rule out economies of scope, i.e., the fixed cost of adding a particular flavor does not change with the products that are already being offered.

Firm b's objective is to maximize the profit from the staples and the optional flavors that it offers (as indicated by $d_{bt} = (d_{b1t}, \dots, d_{bO_bt})$):

$$\max_{p_{bt}} (p_{bt} - c_{bt}) M \left(\sum_{f=1}^{O_b} s_{bft}(\cdot) d_{bft} + \sum_{f=O_b+1}^{F_b} s_{bft}(\cdot) \right) - \sum_{f=1}^{O_b} \phi_{bft} d_{bft}, \tag{3}$$

where M is the size of the market. To simplify the notation, we suppress $(p_{1t}, \dots, p_{Bt}, d_{1t}, \dots, d_{bt})$ as arguments of s_{bft}.

Differentiating yields the competitors' first-order conditions with respect to prices:

$$p_{bt}(d_{1t}, \dots, d_{Bt}) = c_{bt} - \frac{\sum_{f=1}^{O_b} s_{bft}(\cdot) d_{bft} + \sum_{f=O_b+1}^{F_b} s_{bft}(\cdot)}{\sum_{f=1}^{O_b} \frac{\partial s_{bft}(\cdot)}{\partial p_{bt}} d_{bft} + \sum_{f=O_b+1}^{F_b} \frac{\partial s_{bft}(\cdot)}{\partial p_{bt}}}. \tag{4}$$

Solving the system of equations (4) yields equilibrium prices for the specific flavor offerings considered. Because we are dealing with multi-product firms, the conditions for uniqueness outlined in Caplin & Nalebuff (1991) do not necessarily hold.

We emphasize the dependency of prices on flavor offerings by writing $p_{bt}(d_{1t}, \dots, d_{Bt})$ for equilibrium prices. We solve for equilibrium prices for the remaining possible flavor sets analogously. This gives us a vector of $2^{\sum_b O_b}$ different prices for firm b, one for each possible bundle of flavors that could be offered. We let s_{bt} denote brand b's aggregate market share at time t as a function of its and its competitors' flavor offerings, $s_{bt} = \left(\sum_{f=1}^{O_b} s_{bft}(d_{bt}, d_{-bt}) d_{bft} + \sum_{f=O_b+1}^{F_b} s_{bft}(d_{bt}, d_{-bt}) \right)$, where $d_{-bt} = (d_{1t}, \dots, d_{b-1t}, d_{b+1t}, \dots, d_{Bt})$ are the flavor offerings of all brands but b.

2.2 Stage 1

Each firm chooses the optimal set of flavors given its expectation of the other firms' choices and prices under each configuration. Firm b chooses $d_{bt} = (d_{b1t}, \dots, d_{bO_bt})$ to maximize expected profits given by:

$$
\begin{aligned}
& E[\Pi_{bt}(d_{bt}, d_{-bt})] \\
= \; & E\left[(p_{bt}(d_{bt}, d_{-bt}) - c_{bt}) M s_{bt}(d_{bt}, d_{-bt}) - \sum_{f=1}^{O_b} \nu_{bft} d_{bft} \right] \\
= \; & \sum_{d_{-bt}} \left((p_{bt}(d_{bt}, d_{-bt}) - c_{bt}) M s_{bt}(d_{bt}, d_{-bt}) \right) \Pr(d_{-bt}) - \sum_{f=1}^{O_b} \nu_{bft} d_{bft} \\
= \; & \bar{\Pi}_{bt}(d_{bt}) - \sum_{f=1}^{O_b} \nu_{bft} d_{bft}. \qquad (5)
\end{aligned}
$$

The first part of the expression is the expected variable profit and the second represents the fixed costs. Since firm b does not know the fixed costs of its rivals, it cannot predict their flavor offerings with certainty. Hence, firm b forms expectations over its rivals' flavor offerings. In particular, $\Pr(d_{-bt})$ is the joint probability that its rivals offer the particular subset of flavors in d_{-bt}.

The marginal probability that firm b offers bundle d_{bt} is:

$$
\begin{aligned}
\Pr(d_{bt}) &= \Pr\left(E[\Pi_{bt}(d_{bt}; d_{-bt})] \geq E[\Pi_{bt}(d'_{bt}; d_{-bt})] \quad \forall d'_{bt} \in \{0;1\}^{O_b} \right) \\
&= \int_{A(d_{bt})} \prod_{f=1}^{O_b} dG_{bf}(\varepsilon_{bft}); \qquad (6)
\end{aligned}
$$

where we let $A(d_{bt})$ denote the set of values for $\varepsilon_{bt} = (\varepsilon_{b1t}; \ldots; \varepsilon_{bO_bt})$ that induce the choice of flavor bundle d_{bt}:

$$
A(d_{bt}) = \left\{ \varepsilon_{bt} \,\middle|\, \bar{\Pi}_{bt}(d_{bt}) - \bar{\Pi}_{bt}(d'_{bt}) \geq \sum_{f=1}^{O_b} \varepsilon_{bft}(d_{bft} - d'_{bft}) \quad \forall d'_{bt} \in \{0;1\}^{O_b} \right\}. \qquad (7)
$$

Assuming independence across firm cost shocks, ε_{bft}, entails that the joint probability of observing a particular set of product offerings in the market $(d_{1t}; \ldots; d_{Bt})$ is the product of the marginal probabilities for d_{bt} defined in equation (6). Substituting the flavor choice probabilities defined above into each firm's expected profit y0be¯ned above=1 other °avor o®ering d'_{bt}, given its conjecture of its competitors' behavior.

The expressions de¯ned in equations (5) and (6) characterize a system of $\sum_{b=1}^{B} 2^{O_b}$ equations in $\sum_{b=1}^{B} 2^{O_b}$ unknown °avor choice conjectures. We solve for each ¯rm's probability of o®ering a given product assortment by numerically integrating over its unobserved ¯xed cost o_{bt}, as a function of its competitors' assortment choice probabilities. The equilibrium probabilities of o®ering each °avor combination solve the system of equations for all competitors,d

Figure 1: Expected profits.

in a given market. With two flavors, there are four possible choices, offering either, both, or none of the flavors, i.e., we have $d_b = (d_{b1}, d_{b2}) \in \{(0,0),(0,1),(1,0),(1,1)\}$. The firms thus compare four expected profit levels and choose the flavor(s) that corresponds to the highest level of expected profit. Figure 1 illustrates the example.

Suppressing market subscripts for ease of readability, firm 1's expected profit if it chooses flavor 1, or $d_1 = (1,0)$, is given by:

$$E[\Pi_1(1,0,d_{21},d_{22})] = E[(p_1(1,0,d_{21},d_{22}) - c_1) M s_{11}(1,0,d_{21},d_{22})] - \nu_{11}. \qquad (8)$$

Since firm 1 does not observe firm 2's fixed cost, it has to form an expectation of firm 2's optimal flavor choice, that is, a probability assessment of how likely it is that firm 2 chooses any one of its four possible flavor sets. Integrating over firm 2's cost type yields expected profit of the form:

$$\begin{aligned} & E[\Pi_1(1,0,d_{21},d_{22})] \\ = & \sum_{d_{21},d_{22}\in\{0,1\}} \Big(p_1(1,0,d_{21},d_{22}) - c_1\Big) M s_{11}(1,0,d_{21},d_{22}) \Pr(d_{21},d_{22}) - \nu_{11} \\ = & \bar{\Pi}_1(1,0) - \nu_{11}, \qquad (9) \end{aligned}$$

where $p_1(1,0,d_{21},d_{22})$ denotes firm 1's optimal price as determined in stage 2 if it offered flavor 1 and firm 2 offers the flavor set $d_2 = (d_{21}; d_{22})$, while $\Pr(d_{21}; d_{22})$ denotes the probability that firm 2 offers that flavor set. The flavor offering considered by firm 1 and the possible flavors offered by firm 2 are thus reflected in both the price firm 1 charges and its expected market share. Firm 1's expected profit for flavor 2 is computed similarly. As in the entry literature (Bresnahan & Reiss (1991)), we normalize the expected profit from not offering any flavor to zero, yielding the traditional profit threshold crossing condition for offering a flavor.

The expected profit if firm 1 offers both flavors, i.e., chooses flavor set $d_1 = (1; 1)$, is given by:

$$E[\Pi_1(1; 1; d_{21}; d_{22})] = \overline{\Pi}(1; 1) - (\;_{22}$$

triangle spanned by $(b, -c)$, $(a-c, -c)$, and $(b, b-a)$. Hence,

$$
\begin{aligned}
& \Pr(d_2 = (1,0)) \\
= \;& G_{21}(b)(1 - G_{22}(-c)) - \int_{\varepsilon_{21}=a-c}^{b} \int_{\varepsilon_{22}=-c}^{\varepsilon_{21}-a} g_{22}(\varepsilon_{22}) d\varepsilon_{22} g_{21}(\varepsilon_{21}) d\varepsilon_{21} \\
= \;& G_{21}(b)(1 - G_{22}(-c)) - \int_{\varepsilon_{21}=a-c}^{b} (G_{22}(\varepsilon_{21} - a) - G_{22}(-c)) g_{21}(\varepsilon_{21}) d\varepsilon_{21} \\
= \;& G_{21}(b)(1 - G_{22}(-c)) + G_{22}(-c)(G_{21}(b) - G_{21}(a-c)) \\
& + \int_{\varepsilon_{21}=a-c}^{b} G_{22}(\varepsilon_{21} - a) g_{21}(\varepsilon_{21}) d\varepsilon_{21}. \qquad (13)
\end{aligned}
$$

The above presumes $b \geq a - c$. If $b < a - c$, then the probability simplifies to:

$$\Pr(-\varepsilon_{22} < c, \varepsilon_{21} < b, \varepsilon_{21} - \varepsilon_{22} < a) = G_{21}(b)(1 - G_{22}(-c)).$$

Depending on the distribution assumed for G_{21} and G_{22}, a closed-form solution for these probability expressions may not exist. However, one can easily find the probabilities using numerical integration techniques.

The probability that flavor 2 is chosen over no flavor, flavor 1, or flavors 1 and 2 together is obtained analogously. The probability that firm 2 offers both flavors, flavors 1 and 2, is given by:

$$
\begin{aligned}
\Pr(d_2 = (1,1)) \;=\; & \Pr(\varepsilon_{22} < \pi_2(1,1) - \pi_2(1,0) \wedge \varepsilon_{21} < \pi_2(1,1) - \pi_2(0,1) \\
& \wedge \varepsilon_{21} + \varepsilon_{22} < \pi_2(1,1)), \qquad (14)
\end{aligned}
$$

while the probability that firm 2 chooses not to offer any flavors equals

$$\Pr(d_2 = (0,0)) \;=\; \Pr(\varepsilon_{21} > \pi_2(1,0) \wedge \varepsilon_{22} > \pi_2(0,1) \wedge \varepsilon_{21} + \varepsilon_{22} > \pi_2(1,1)). \qquad (15)$$

Equations (11), (14) – (15) together with their analogues for firm 2's assessment of firm 1's probabilities form a system of 8 equations in the 8 unknown equilibrium probabilities.

The two-by-two model illustrates the computational demands of solving and estimating the model. In particular, the number of profit scenarios that have to be computed and the dimension of the fixed point go up exponentially in number of flavors. In the above example with $O_1 = O_2 = 2$, there are $2^4 = 16$ scenarios for

Figure 2: Regions of integration and product o®erings.

pro¯ts. Each ¯rm has $2^2 = 4$ possible assortments. If we added one more °avor, say, $O_1 = 3$ and $O_2 = 2$, then there would already be $2^5 = 32$ scenarios for pro¯ts, so

Aggregating the data leaves us with 1600 observations (25 months, 64 markets) for each UPC.

We declare a product available in a given market and period if there are nonzero sales for this particular brand-°avor combination. Thus, another compelling reason to aggregate to the monthly level is to avoid situations where a particular brand/°avor is on some store shelves, but does not record any sales over a short period of time. In constructing the monthly sample, we veri¯ed that we did not lose important weekly variation in °avor availability. We computed for each of the optional °avors the number of weeks in the month that the product was available in a particular market. In approximately 97 percent of the market-month observations, the °avor appeared in the data in either all or none of the weeks in that month. For the remaining three percent of market-month observations, we assume that the °avor is available, even though it appears in the data in only three weeks (1.3% of the data), two weeks (0.8%), or one week (0.9%) in that month. Treating the °avor as unavailable in these instances did not change the empirical ¯ndings.

Ice cream is one of the most popular categories in supermarkets: 92.9% of households in the United States purchase in the category (IRI Marketing Factbook, 1993). In the general category of ice cream, there is a distinction between ice cream, frozen yogurt, sherbet and sorbet. Depending on butterfat content, ice cream is further disaggregated into superpremium, premium, and economy categories. While a half-cup serving of HÄagen Dazs Vanilla Bean ice cream, a superpremium °avor, has 18 grams of fat and 290 calories, the equivalent serving of Dreyers, a premium brand, has only 8 grams of fat and 140 calories. Furthermore, ice cream is o®ered in a multitude of package sizes, fat and sugar content levels. Figure 3 presents an overview.

Regular fat ice cream accounts for 86% of ice cream sales, and only 7.5% of all ice cream sold has reduced or no sugar content. The most popular size is 4 pints with about 48% of all sales, followed by the closely related 3.5 pint size with 29%,[8] and 1 pint with 15%. Most of the superpremium ice cream brands such as Ben & Jerry's and HÄagen Dazs are sold almost exclusively in the smaller, 1 pint tubs, whereas the other brands are usually sold in larger sizes.

Figure 3: Dollar shares of ice creams by fat content, sugar content, and package size.

ice cream (i.e., full fat and regular sugar) in the premium category, and in particular on the decisions of the two leading national brands – Breyers and Dreyers – pertaining to their assortment of vanilla flavors in the most popular family size of 3.5/4 pints. Vanilla flavors represent up to one-third of total category sales. Our data reveal a total of 22 different varieties of vanilla ice cream, involving subtle differences in the ingredients. For example, Vanilla Bean flavors contain visible specks of vanilla, while French Vanillas have a higher egg content. The most popular vanilla varieties in the data are “French Vanilla,” “Vanilla,” “Vanilla Bean,” “Natural Vanilla,” and “Extra Creamy Vanilla.” We do not include flavors with substantial additional ingredients or flavorings, such as Cherry Vanilla or Vanilla Fudge. Because manufacturers do not “specialize” in vanilla, but the number of vanilla flavors is highly correlated with the total number of flavors offered, an analysis of the vanilla market should shed considerable light on the firms' product assortment decisions in general.

Table 1 presents a market structure snapshot across the 64 geographic regions in our data set. For the purposes of this analysis, we have classified brands that do not have at least five percent market share in at least five percent of the markets (i.e., three markets) as “other.” For each brand, the table presents the number of markets out of 64 for which the brand has each particular market share position. Note that the entries for \Private label" and \Other" in Table 1 are aggregates of all the private label (other brands) that are available in di®erent regions and in di®erent stores within a region. Hence, their competitive position is overstated.[9]

Breyers and Dreyers[10] are the only premium brands that are truly national and have a presence in all markets. However, given the production requirements and distribution economics associated with ice cream, many regional manufacturers established in the early and middle parts of the 20^{th} century have maintained their market position through the present. Brands such as Hood in the Northeast, Blue Bunny in the Midwest and the Southeast, and Tillamook in the Paci¯c Northwest have substantial sales; indeed, they are holding the top share in several markets. In addition, sales of private label brands vary in importance from one region to the next.

Table 1: Market share rank of manufacturers. across the 64 regional ice cream markets.

	Number of Markets					
Market Share Rank:	1st	2nd	3rd	4th	5th-10th	Total
Breyers	14	21	23	5	1	64
Dreyers	5	11	14	20	14	64
Deans	0	0	0	1	10	11
Friendly	1	0	3	0	11	15
Hiland	0	2	0	0	5	7
Hood	1	2	0	2	3	8
Kemps	1	1	0	0	8	10
May¯eld	1	1	2	2	6	12
Pet	0	0	2	4	5	11
Prairie Farms	1	0	1	0	10	12
Tillamook	0	1	0	2	0	3
Turkey Hill	1	1	1	1	10	14
United Dairy	0	1	1	1	7	10
Wells Blue Bunny	3	0	4	6	15	28
Yarnells	1	0	0	2	2	5
Private Label	30	15	10	5	4	64
Other	5	8	3	13	32	61

variation that can be helpful in identi¯cation of the model parameters.

Importantly, there is variation in the availability of some of the vanilla °avors for Breyers and Dreyers across geographic regions and months. Table 3 provides the details. Natural Vanilla, French Vanilla and Extra Creamy Vanilla for Breyers and Vanilla, French Vanilla and Vanilla Bean for Dreyers are (almost) always available and can thus be treated as staples. Breyers Homemade Vanilla and Dreyers Natural Vanilla, Double Vanilla and Vanilla Custard are the optional °avors, whose o®ering varies widely by markets and periods. Double Vanilla was introduced towards the end of our sample period, so it is a somewhat special case. Since we do not model the nationwide rollout of a new product, we drop it from the product-choice analysis. We also drop Breyers Vanilla because it only appears in two markets and a few months.

Table 4 illustrates the distribution of the market shares of Breyers and Dreyers' vanilla °avors conditional on them being o®ered, along with the percentage of market-months in which they are o®ered. Given that all °avors have the same price and marginal cost of production, the market share of a °avor is indicative of its pro¯tability (prior to ¯xed costs) within the brand. A comparison of average market shares and availabilities shows that more pro¯table °avors tend to be o®ered more often. The correlation between average market share and the percentage of months o®ered is 0.5619. Among optional °avors, Dreyers Vanilla Custard has the lowest market share (0.0078) and is o®ered the least frequently (43.40%) while Breyers Homemade Vanilla has the highest market share (0.00344) and is o®ered the most frequently (86.50%).

These correlations, albeit based on small samples of °avors, provide some evidence that the role of unobserved demand shocks that a®ect both the availability and the market share of a °avor is limited in our application. Such demand shocks could result in a negative correlation between shares and availabilities due to rarely o®ered °avors capturing high market shares when o®ered.

Table 5 presents a summary of the market shares and prices for the brands included in the demand analysis. Breyers is the clear market leader with an average market share of 21%, followed by Dreyers with a market share of almost 14%. Tillamook, Turkey Hill and Yarnells have also sizeable shares in their markets, re°ecting their position as strong - albeit small - regional players. The brands vary in their pricing strategies. Breyers and Dreyers occupy the middle ground, while many regional players have lower (Hood, Pet, Turkey Hill) or higher (Tillamook, Kemps) average prices.

Table 2: Distribution of °avor availability for regional manufacturers across markets/months in the data set.

	Market-month obs.	# of °avors	# markets	% of market-months in which # of °avors is o®ered: 0	1	2	3	4	5	6
Wells Blue Bunny	700	4	28	0.1	-	-	27.7	72.1	-	-
Friendly	375	3	15	-	-	14.9	85.1	-	-	-
Turkey Hill	350	3	14	-	-	2	98	-	-	-
Prairie Farms	300	3	12	1	-	9.7	89.3	-	-	-
May¯eld	300	4	12	-	-	1.7	6	92.3	-	-
Deans	275	4	11	-	-	66.9	24	9.1	-	-
Pet	275	3	11	1.8	-	0.7	97.5	-	-	-
Kemps	250	6	10	3.2	4	22.8	10	11.6	20.8	27.6
United Dairy	250	4	10	-	1.6	16.4	80.4	1.6	-	-
Hood	200	3	8	-	-	24	76	-	-	-
Hiland	175	6	7	0.6	2.3	2.3	5.1	46.9	18.3	24.6
Yarnells	125	4	5	10.4	1.6	4.8	36.8	46.4	-	-
Tillamook	75	2	3	-	-	100	-	-	-	-

Table 3: Percentage of months in which a °avor is available in a geographic market.

	Breyers	Dreyers
Market		

Table 4: Market Share of Breyers and Dreyers Flavors Conditional on O®ering

	Mean	Std. Dev.	Min.	Max.	% of Market Months O®ered
Breyers					
Extra Creamy Vanilla	0.0831	0.0329	0.0054	0.1541	99.30%
French Vanilla	0.1469	0.0322	0.0722	0.2287	100.00%
Homemade Vanilla	0.0344	0.0348	0.0004	0.1508	86.50%
Natural Vanilla	0.3765	0.1046	0.1817	0.5618	100.00%
Vanilla	0.0102	0.0177	0	0.0307	0.40%
Dreyers					
Double Vanilla	0.0392	0.0201	0.0004	0.0868	25.20%
French Vanilla	0.0921	0.0383	0.0223	0.1895	99.50%
Natural Vanilla	0.0295	0.0273	0.0018	0.1365	62.00%
Vanilla	0.1176	0.0788	0.0013	0.3026	97.40%
Vanilla Bean	0.1156	0.0541	0.0034	0.2532	98.00%
Vanilla Custard	0.0078	0.0073	0.0001	0.0382	43.40%

Table 5: Market shares and prices of brands included in the analysis.*

	Market Share		Price	
	average	std. dev.	average	std. dev.
Breyers	0.2118	0.0983	$3.78	$0.49
Dreyers	0.1379	0.0873	$3.43	$0.51
Deans	0.0236	0.0320	$3.64	$0.74
Friendly	0.0838	0.0724	$3.46	$0.62
Hiland	0.0563	0.0907	$3.53	$0.54
Hood	0.0898	0.1052	$2.80	$0.51
Kemps	0.0365	0.1054	$4.01	$1.01
May¯eld	0.0812	0.1080	$3.90	$0.66
Pet	0.0484	0.0562	$3.05	$0.54
Prairie Farms	0.0393	0.0739	$3.25	$0.54
Tillamook	0.1184	0.0491	$4.14	$0.48
Turkey Hill	0.1090	0.1049	$3.16	$0.54
United D93 D93				

As mentioned above, the IRI data include measures of units sold and revenue (with which we calculate average prices) for each UPC in each market. To estimate the econometric model, we complement these data with information drawn from a variety of sources. Table 6 outlines the variables, their sources, and the level of aggregation. For example, the data that we have on individual demographics are from the 2000 Census - these data vary across geographic markets, but not over time. We have monthly information on several input cost measures; some (e.g., fuel prices) also vary across geographic markets while others (e.g., cost of capital represented by the commercial paper rate) do not. We have calculated the distance from each geographic market to the nearest production facility for Breyers and Dreyers. These are the only data that vary across the manufacturers (but are the same in each time period).

The panels of Table 6 are split based on the way we use these additional variables. The top section of the table includes market demographics and temperature; we think that these may be associated with ice cream demand. There may be di®erences in input costs as well - the variables in the second panel possibly in°uence the costs of manufacturing and/or distributing the product. In the bottom panel, we have included some statistics on the market structure of complementary industries that may a®ect the ice cream market on either the supply or the demand side. Prices and measured quantities sold in supermarkets may be a®ected if there are more Wal-Mart stores in the local market. Since manufacturers rely on distributors that are speci¯cally equipped to transport frozen dairy products, the market structure of these distributors may also be relevant.

4 Empirical Strategy

Below we ¯rst give details on the speci¯cation of our empirical model, which di®ers from the model presented in Section 2 by fully accounting for regional and private label brands in the demand estimation. We thus no longer assume that exactly the same brands appear in both stages of the game. We then discuss the estimation procedure in more detail.

Table 6: Summary of Non-IRI Data.

Variable	Source	Level of Variation	Mean	Std. Dev.
Demographic and Demand Variables:				
Population	2000 U.S. Census	Market	3,164,796	3,044,238
% African American	2000 U.S. Census	Market	0.124	0.097
Avg. household size	2000 U.S. Census	Market	2.560	0.141
Per capita income	2000 U.S. Census	Market	21,831.210	2,917.420
% under 18	2000 U.S. Census	Market	0.257	0.019
% 18-24 years	2000 U.S. Census	Market	0.098	0.011
% 25-44 years	2000 U.S. Census	Market	0.306	0.018
% 45-64 years	2000 U.S. Census	Market	0.219	0.013
% over 65	2000 U.S. Census	Market	0.121	0.024
% Males	2000 U.S. Census	Market	0.489	0.006
Temperature	NOAA	Market & Month	67.454	17.245
Measures of Various Input Costs:				
Commercial paper rate	Datastream	Month	2.035	0.951
Cream II ($ per lb)	Dairy Market News	Month	2.247	0.405
Nonfat dry milk ($ per lb)	Dairy Market News	Month	0.926	0.092
Sugar (cents per lb)	Bloomberg	Month	9.039	1.560
Manufacturing wage (NAICS 3115)	Bureau of Labor Statistics	Month	688.407	17.316
Fuel Price ($ per gallon)	Energy Information Administration	Market & Month	147.471	31.746
Distance from closest production facility to market (Breyers)	Own calculations	Market & Firm	283.815	200.063
Distance from closest production facility to market (Dreyers)	Own calculations	Market & Firm	321.364	207.822
Market Structure - Complementary Industries:				
# of Wal-Mart stores	Own calculations	Market	26.594	17.112
Local distributors (NAICS 424330) - population per establishment	County Business Patterns	Market	152,667	56,801
Local distributors (NAICS 424330) - share of employment in top-4 ¯rms	County Business Patterns	Market	0.492	0.201

4.1 Econometric Specification

We define the potential market size based on the total supermarket sales of regular, 3.5/4 pint ice cream in each market and calculate the shares of the competing brands relative to this size M.[11] While we consider only Breyers and Dreyers at the product-choice stage, our demand model also includes private labels and regional players. The utility of these alternatives is specified in the same way as for the branded flavors in equation (1). We assume that the prices for these alternatives are set in a noncomponents - dairy, packaging, and wages - are likely constant within regions and across manufacturers, consistent with our notion that these costs are common knowledge across players. In our empirical specification, we include as marginal cost shifters in w_{bt} a brand-specific constant, transportation costs (distance between the market and a brand's closest distribution center, average fuel cost), input prices (sugar, cream, dry milk, the local average weekly wage, and the commercial paper rate), and distribution costs (measures of market structure in local distribution: population per local distributor and share of employment in the top 4 local distributors).

The inclusion of the regional players in the demand model results in differences in variable profit for a particular optional flavor offered by Breyers or Dreyers across markets. Variable profits depend on marginal cost shifters, demographics, and the entire set of rivals' products. Since regional players and their offerings differ across markets, the differences in the degree of substitution between the regional players' flavors and those of the national players result in differences in the profitability of a particular flavor that results in different flavor offering probabilities across markets.

We assume that the flavor-specific fixed offering costs are drawn from a log-normal distribution with brand-flavor specific scale and shape parameters and a location parameter of zero, i.e., $G_{bf} = \ln(\mu_{bf}; \sigma^2_{bf})$, where μ_{bf} and σ^2_{bf} denote the parameters of the normal distribution of the log of ν_{bf}. We use the log-normal distribution as a flexible distribution that ensures positive fixed costs and that allows us to compute in a tractable fashion the distribution of fixed costs when firms offer both flavors and the fixed costs equal to the sum of the two flavors' fixed costs. The mean of the distribution, $\exp\left(\mu_{bf} + \frac{1}{2}\sigma^2_{bf}\right)$, captures all factors that determine product assortment choices that are not accounted for in the average estimate of variable profits, while its standard deviation captures deviations from the average decision across markets/months.

4.2 Estimation

For a given set of parameters for the demand and pricing equations, the second stage of the model yields predicted market shares for the flavors offered in a given market. These market share values are then scaled by our estimates of market size M. In addition, the pricing stage generates estimates of marginal costs that the observed prices and the assumption of Bertrand-Nash pricing imply.[13] These marginal costs

[13] The data for one of the markets, Little Rock, AR, was suspect because Dreyers was not at all present for a couple of quarters. For this reason we could not back out marginal cost as described,

Figure 4: Breakdown of manufacturing cost in the ice cream industry. 1997 Economic Census.

°ow into the ¯rst-stage pro¯t function to determine pro¯ts of all potential assortment choice combinations. The ¯rst stage then focuses on determining an equilibrium probability

°ow in7(y)imaed.

Our ¯rst set of moment conditions is thus the sum of squared deviations of predicted from observed market shares:

$$Q_{1b}(\mu) = \sum_t e^s_{bt}(e^s_{bt})$$

problem into smaller pieces. First we obtain the demand parameters. Given the demand parameters, we estimate the marginal cost coe±cients. Finally, with both demand and marginal cost parameters in hand, we obtain the ¯xed cost.[14]

To calculate the objective function we draw a large number of ¯xed costs (S = 5000) and obtain a nonparametric estimate of the frequency with which a ¯rm o®ers a particular assortment given its beliefs about its rival's o®erings. Because the frequency count can jump even for small changes in the parameter values, the objective estimation run is based on starting values of 0:0001 for all parameters), our procedure yields average estimates that are very close to the true values.[15]

5 Estimation Results

Demand and Marginal Cost. Table 7 presents the parameters of the demand and pricing equations for the ice cream data. As a baseline, we include a homogeneous logit model that allows for separate brand-°avor dummies for all o®ered °avors (not reported in the table). The second column in Table 7 contains our main random-coe±cients demand speci¯cation. The majority of estimated coe±cients is stable across the two speci¯cations. The demand for each °avor falls in the brand's price, with an implied elasticity ranging from ¡2:01 to ¡1:52 for the homogeneous logit model and ¡2:02 to ¡1:40 for the random-coe±cients logit model, which is comparable to other frequently purchased consumer goods in mature categories.

In addition we control for variables that shift demand for all inside goods relative to the outside option such as market demographics and time dummies. Our estimates indicate that there is statistically signi¯cant seasonal and geographic variation in the demand for vanilla °avors in supermarkets. In addition, the demographic composition of a market has a pronounced impact on demand: Markets with a higher percentage of males and African Americans tend to have higher demand for vanilla ice cream (lower demand for the outside good).

Most aggregate marginal cost shifters, such as the price of sugar and dry milk, are not statistically signi¯cant, possibly due to the lack of variation across markets and brands. As expected, marginal costs increase in brand-speci¯c transportation (distance to the nearest distribution facility) and fuel costs, as well as the proxies for the size and density of the local distribution network.

Fixed Cost. Reasonable starting values for the °avor ¯xed cost distributions should re°ect variation in actual ¯xed costs. To determine the likely magnitude for these costs, we use the following procedure. Beginning with initial estimates for demand and marginal cost, we calculate variable pro¯ts for each possible o®ering. We then loop through °avors and use data on whether the °avor is o®ered to infer bounds on ¯xed costs that would make the observed °avor o®ering decision optimal ex-post. This

[15]Results available from the authors upon request.

Table 7: Demand and marginal cost estimates using ice cream data.

	Homogeneous Logit Model		Random Coe±cients Logit Model	
	Estimate	Std. Error	Estimate	Std. Error
Demand { Inside °avors				
Price	-0.5019	0.0209	-0.5070	0.0264
Price SD			0.0623	0.0158
Breyers constant			0.7958	0.1853
Breyers SD			0.1081	0.0813
Dreyers constant			-0.5733	0.1791
Dreyers SD			0.1455	0.1280
Demand { Outside option				
Temperature	0.0009	0.0011	0.0087	0.0018
January dummy	-0.0080	0.0448	0.0048	0.0088
February dummy	0.0880	0.0384	0.0544	0.0591
March dummy	0.1193	0.0441	-0.0765	0.0603
April dummy	0.0762	0.0448	-0.2425	0.0466
May dummy	0.1198	0.0496	-0.2559	0.0608
June dummy	0.1121	0.0560	-0.3904	0.0643
July dummy	0.1134	0.0545	-0.4421	0.0674
August dummy	0.1306	0.0641	-0.2518	0.0719
September dummy	0.0745	0.0580	-0.3650	0.0666
October dummy	0.0689	0.0479	-0.1748	0.0546
November dummy	-0.0747	0.0453	-0.0227	0.0363
Northeast dummy	0.6097	0.0449	-0.5940	0.0483
Midwest dummy	0.3090	0.0365	-0.4844	0.0371
South dummy	0.4451	0.0418	-0.4895	0.0505
% African American	-1.1401	0.1566	-0.1863	0.1614
% Male	-9.6801	1.7030	-21.3949	0.5949
% 18-24 old	-4.4395	1.4749	1.6635	1.5779
% 25-44 old	-3.7634	1.5196	-3.6254	1.2495
% 45-64 old	-2.9410	1.3352	-2.2134	1.3165
% 65 and older	-8.0026	0.9295	-1.7608	0.8625
Average household size	0.2340	0.1461	-0.7608	0.0955
Per capita income	-0.0001	1.1E-05	0.0001	6.7E-06
Wal-Mart	0.0015	0.0007	-0.0041	0.0009
Marginal cost:				
Breyers constant	5.2320	0.9258	4.5881	0.9104
Dreyers constant	4.8952	0.9254	4.2710	0.9099
Transportation cost	0.0002	3.2E-05	0.0002	3.2E-05
Sugar price	-0.0027	0.0252	-0.0057	0.0244
Wage	-0.0037	0.0014	-0.0040	0.0013
Commercial paper	-0.0108	0.0600	-0.0035	0.0587
Cream II price	-0.1180	0.0512	-0.1180	0.0503
Dry milk price	-0.2712	0.2043	-0.2916	0.2031

Table 8: Distribution parameters of log ¯xed cost estimated from ice cream data. Normal distribution.

Parameter	Estimate	Std. Error*	Con¯dence Interval*	
Mean μ_{bf}				
Breyers Homemade Vanilla	5.5397	0.2555	4.9245	6.0253
Dreyers Natural Vanilla	8.3850	0.1221		

Table 9: Implied means, standard deviations, and medians of estimated ¯xed costs.

Parameter	Estimate	Con¯dence Interval*	
Mean			
Breyers Homemade Vanilla	3340.9	1759.8	6353.6
Dreyers Natural Vanilla	28447.0	15959.2	46020.1
Dreyers Vanilla Custard	2302.1	1103.1	4844.8

cost, however, the single-°avor options hold relatively steady assortment shares, while the option of o®ering neither of the two °avors continues to grow in likelihood. This ¯nding suggests that the two °avors substitute for each other, such that with high ¯xed cost, demand is not su±cient to o®er both, but more than outweighs the ¯xed cost of o®ering only one of the two °avors. We investigate the role of di®erentiation between optional °avors in greater detail in the next section.

6 Policy Experiments

We demonstrate the economic signi¯cance of the estimated structural parameters in several illustrative analyses. First, because we explicitly model demand to derive the variable pro¯ts that drive ¯rms' product choices, we can study how changes in demand a®ect assortment choices; i.e., changes in heterogeneity in preferences or willingness to pay can be traced through to ¯rms' responses in °avor o®erings. Second, our model allows ¯rms to adjust their product o®erings optimally in response to a change in the competitor's assortment. We illustrate the advantages of this approach in a merger simulation.

Horizontal Di®erentiation

Given the logit speci¯cation for consumer demand in equation (1), we can investigate the role of horizontal preference heterogeneity by varying the logit scale parameter, ¾ (Anderson, de Palma & Thisse 1992). In estimation, we normalize ¾ to one. In a counterfactual, we compute how market shares, mark-ups, and ultimately assortment choices respond to changes in ¾ (or equivalently, to rescaling all demand estimates).

We ¯nd that as the heterogeneity in consumer tastes increases, both Breyers and most frequently o®ered stand-alone product since its °avor preference and thus profitability are ampli¯ed, now balancing its ¯xed costs. Most frequently, however, with a su±ciently high degree of horizontal product di®erentiation, both °avors make up Dreyers' optimal portfolio.

Vertical Di®erentiation

Next we consider the e®ect on each brand's assortment of increasing the dispersion in the °avor constants for each brand's set of optional and staple vanilla °avors included in the demand system. A brand may consider what extent of vertical di®erentiation (i.e., variation in the perceived quality) among its °avors is optimal. On one hand, o®ering a large array of options may appeal to a set of consumers with di®ering willingness to pay. On the other hand, o®ering options of vastly di®ering quality may dilute the brand image. Thus if a brand can invest in promotion e®orts, would it pay o® to focus on only some o®erings to attempt to increase the degree of vertical di®erentiation of the product line? Alternatively, if a brand decides to extend its product line, is it bene¯cial to add a product of similar quality to the line?

We vary the degree of vertical di®erentiation between each brand's °avors by decomposing the contribution of the brand and °avor constants into the mean brand e®ect $\beta_b + \bar{\delta}_{b:}$ (9.83 for Breyers and 5.60 for Dreyers) and deviations from the mean, where β_b denotes the estimated brand constant and $\bar{\delta}_{b:}$ denotes the mean °avor constant. Thus, $\beta'_{bf} = \lambda_b(\beta_{bf} - \bar{\delta}_{b:}) + \bar{\delta}_{b:} + \beta_b$. Our model estimates above are based on a speci¯cation where $\lambda_b = 1$. We vary the dispersion in brand-°avor constants by increasing λ_b from zero, equivalent to there being no vertical di®erentiation between the brand's °avors, to a value of ten, which corresponds to signi¯cantly more vertical di®erentiation than in our estimates. In particular, if a given °avor dummy is estimated to be above (below) average for the brand, then it becomes more (less) attractive for $\lambda_b > 1$. By construction, we leave the average preference for the brand, and therefore the attractiveness of the brand's entire portfolio, unchanged.

As above, we use the estimated random-coe±cient demand, marginal, and ¯xed cost parameters, together with varying values for λ_b, to trace out how the product assortment of each brand changes as the degree of vertical di®erentiation in its °avors changes. Figure 6 illustrates the e®ect that increasing vertical di®erentiation in its °avors has on Breyers' own assortment choices, as well as the competitive e®ect of such a change on Dreyers' assortment choice.

Table 10: Flavor Constants

	Breyers		Dreyers	
	Estimated Constant	Implied Brand-Flavor Value	Estimated Constant	Implied Brand-Flavor Value
Vanilla	10.1082*	10.9040	10.1082*	9.5349
French Vanilla	9.1267*	9.9225	9.1267*	8.5534
Natural Vanilla	9.8130*	10.6088	9.8130*	9.2397
Homemade Vanilla	7.7256*	8.5214		
Extra Creamy Vanilla	8.3811*	9.1769		
Vanilla Bean			9.9889*	9.4156
Vanilla Custard			5.8449	5.2716
Double Vanilla			-7.8658	-8.4391

Note: Recall that Breyers constant is 0.7958 and Dreyers is -0.5733. * Denotes signi¯cance at the 5% level.

To see the own-brand e®ects, consider the case of Breyers. The estimated brand and °avor e®ects for the optional °avor that we consider in the product choice stage (Homemade Vanilla) are below Breyer's average of 9.83, with a value of 8.52 (see Table 6 for the °avor point estimates and implied values for the brand-°avor combinations). The vertical preferences for the °avor thus falls as we increase the degree of vertical di®erentiation in the product line ($\lambda_{Breyers}$). Panel 1 in Figure 6 illustrates that in response Breyers is increasingly likely not to o®er the °avor, an e®ect that is magni¯ed by the ¯xed costs that Breyers pays for o®ering the °avor (which is normalized to zero for all other °avors). The probability that Homemade Vanilla is o®ered decreases monotonically. In general, as λ goes to in¯nity, we would expect only the top °avor of a brand to be o®ered.

The bottom panel in Figure 6 shows that there is also a competitive e®ect of the varying degree of Breyers' vertical product di®erentiation on Dreyers' assortment choices. As the degree of vertical product di®erentiation rises, it puts downward pressure on the single price that Breyers charges for all its °avors. Since in the Bertrand pricing game prices are strategic complements, Dreyers' price declines as well. The associated decline in variable pro¯t implies that Dreyers can no longeras significantly to increases in Breyers' vertical differentiation, suggesting that as the full assortment is slowly removed from the market, some of the demand for the removed flavor is redirected to the remaining optional flavor.

Merger Analysis

One compelling reason to model endogenous product choice together with demand is to generate more accurate merger simulations. As discussed previously, simulations based on demand models that do not allow for the possibility of a change in the composition or characteristics of the post-merger product portfolios do not necessarily reflect the firm's optimal behavior. Our model permits a more accurate simulation, as both price and the set of offered products can be optimally adjusted. To illustrate

Table 11: Merger Simulations.*

	All Flavors & Firms			Breyers & Dreyers' Optional Flavors Only					
				Estimated Fixed Cost			High Fixed Cost		
		Merged Firm			Merged Firm			Merged Firm	
	Duopoly	Fixed Products	Endog. Choices	Duopoly	Fixed Products	Endog. Choices	Duopoly	Fixed Products	Endog. Choices
Price, Breyers	3.785	3.846	3.846	4.549	6.329	6.283	4.763	5.980	5.761
Price, Dreyers	3.427	3.530	3.530	4.842	6.027	6.003	4.764	5.552	5.508
Total pro¯ts, Breyers	8.379	8.392	8.392	3.260	3.348	3.394	2.174	2.240	2.330
Total pro¯ts, Dreyers	4.721	4.723	4.723	5.307	6.480	6.461	3.790	4.438	4.540
Industry total pro¯ts	13.101	13.115	13.115	8.567	9.828	9.855	5.964	6.678	6.871
Pro¯ts, opt. °avors, Breyers	4.392	4.408	4.231	3.260	3.348	3.394	2.174	2.240	2.330
Pro¯ts, opt. °avors, Dreyers	7.497	7.518	7.452	5.307	6.480	6.461	3.790	4.438	4.540
Number of °avors	1.999	1.999	1.980	2.550	2.550	2.483	1.581	1.581	1.435
Share of time o®ered:									
Natural Vanilla	0.865	0.865	0.862	0.975	0.975	0.951	0.611	0.611	0.535
Homemade Vanilla	0.628	0.628	0.619	0.869	0.869	0.841	0.587	0.587	0.553
Vanilla Custard	0.507	0.507	0.498	0.706	0.706	0.691	0.384	0.384	0.347
Consumer surplus	14.730	14.651	14.628	14.906	14.074	14.055	14.048	13.662	13.657

increase in the ¯xed cost of o®ering a °avor.

Our \¯xed products" merger simulation generates reasonable ¯ndings in line with other studies using similar methodology. Comparing the ¯rst two columns of each panel, prices and pro¯ts are higher for the merged ¯rm than for competing duopolists, while consumer surplus is lower. By construction, the number of °avors is the same in each of the ¯rst two columns. When no longer constrained, total industry pro¯ts are (necessarily) higher, as the newly merged ¯rm chooses to o®er a di®erent assortment some of the time. The post-merger product assortment depends critically on the interplay between the °avors' pro¯tability and the level of the ¯xed costs of offering additional °avors. For our empirical setting, the di®erences between the ¯xed and endogenous products scenarios are small, re°ecting the small market share of the optional °avors. With a higher base value of consuming vanilla, the di®erences between the ¯xed and endogenous products cases are more pronounced, in particular as the ¯xed cost of o®ering a °avor increases.

In the scenarios depicted in the two right panels of Table 11, the number of °avors o®ered decreases once we allow for post-merger assortment adjustments, and more so with higher ¯xed costs. The changes in assortment a®ect all °avors whose o®ering probabilities decrease uniformly. The adjustment in assortments also entails a change in market share and correspondingly, a change in average prices. In both scenarios, the average price falls slightly relative to the ¯xed product case. Incorporating endogenous product choice into the merger analysis thus has two e®ects on consumer surplus; it falls in response to the decrease in variety that the merged ¯rm o®ers, but rises in response to the lower prices of the changed variety. Our results suggest that on net, the loss due to decreased variety dominates, resulting in a consumer surplus that is comparable to but slightly lower than the consumer surplus obtained in the ¯xed products analysis.

These simulated merger results also give some idea about magnitudes; in particular, whether ignoring product assortment endogeneity generates substantial changes between the ¯xed and endogenous assortment results (as compared with the di®erences between the duopoly and the ¯xed products monopoly scenarios). As such, one could interpret the results in Table 11 as suggesting that ignoring product choice has minimal e®ect if the ¯xed costs to o®ering each product are low. However, it is important to recognize that the example constrains the merged ¯rm to optimize only among the previously o®ered °avors. In a case where the merged ¯rm has the entire Hotelling line available to choose from (as in Gandhi et al. (2006)) or a larger °avor choice set at its disposal, the impact is likely to be more substantial. Additional market participants may also re-optimize portfolios post-merger, generating more changes to surplus and pro¯ts. Nonetheless, this exercise clearly demonstrates the importance of endogenizing product choice in the context of a policy simulation.

The results in any speci¯c case will rely critically on the estimated parameters firms often choose a different set of products than those previously offered, generating higher profits. The impact of abstracting from endogenous product choice may or may not be large, depending on the estimated cost and demand parameters. What is clear though is that sometimes we reach fundamentally different conclusions by modeling joint product assortment and pricing decisions.

Unlike the reduced-form approaches used in the entry literature, by explicitly modeling price competition we show how demand-side factors affect product-assortment decisions. In particular, we investigate the effect of horizontal and vertical differentiation on equilibrium assortments and prices. With increased horizontal differentiation, even small consumer segments can become valuable enough to give firms an incentive to crowd the product space. The effect of a change in vertical product differentiation is more subtle and depends on how exactly consumers value the various products alternatives that a firm may consider offering. There is no doubt, however, that product assortment decisions are not made in a competitive vacuum: As our empirical findings indicate, when a rival's products become more differentiated, the price level in the market may fall and the firm may be inclined to cull the variety offered since variable profits no longer can cover fixed costs.

Our two-stage game partially captures the relative irreversibility of assortment decisions, but ideally the model would also reflect the different periodicity of the pricing and product choice decisions. One may also want to allow for serial correlation in firms' assortment decisions over time. Short of specifying and estimating a fully dynamic model, one could enrich the present model to introduce state-dependence, thus allowing the distribution of fixed costs to differ systematically depending on whether the product has been offered in the previous period.

Another promising venue for future research is to extend the proposed model in order to account for the selection bias in demand estimation in the presence of unobserved product characteristics. The selection bias occurs because firms only offer products with anticipated high demand, i.e., favorable unobservable (to the researcher) characteristics. Modeling firms' product assortment choice explicitly as we do is a potential way to correct for the selection bias, but it requires recovering the full distribution of the unobservable characteristics.

In sum, the contribution of this paper consists of explicitly deriving the variable profits that enter the product-choice decision from a structural model of product-functions typically used in the entry and location choice literature. Given the importance of price in consumer purchase decisions, this is a critical element when attempting to model product assortment decisions and allows for a broader set of applications. In addition, relative to the literature on structural demand models,

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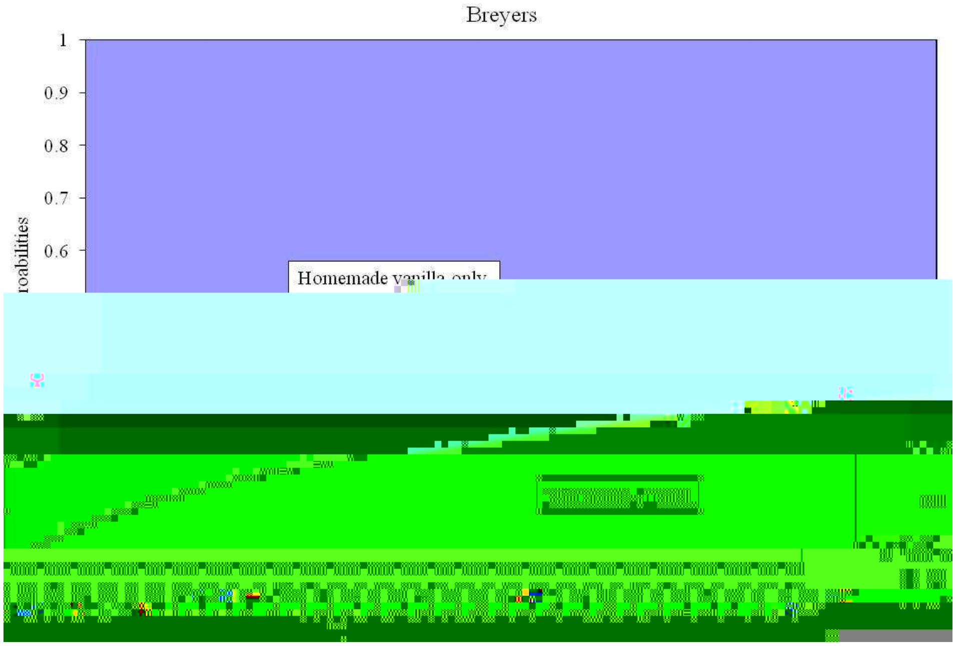

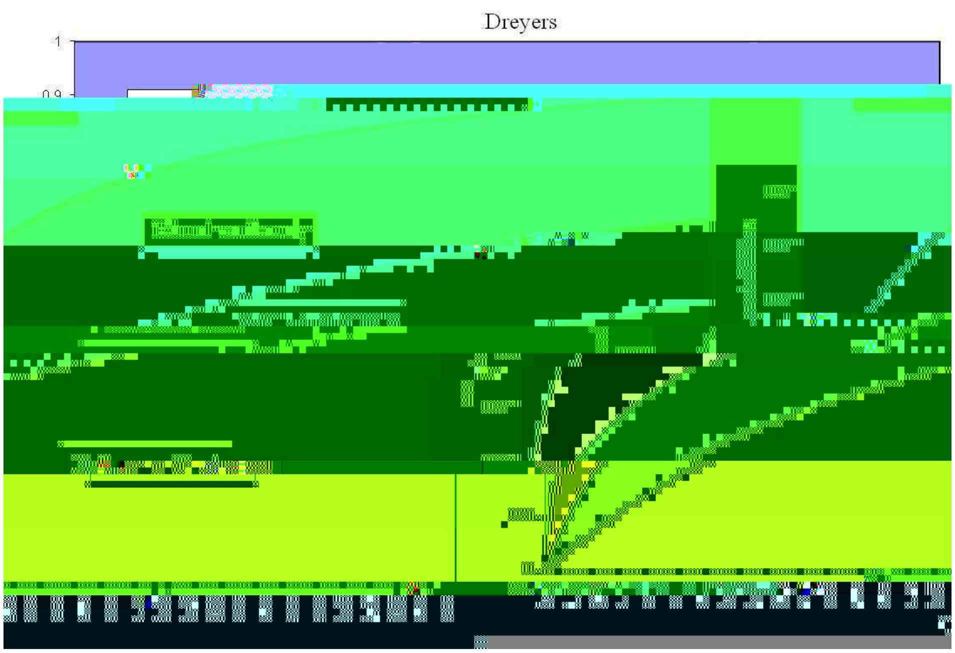

Figure 5: Assortment probabilities as a function of level of ¯xed costs.

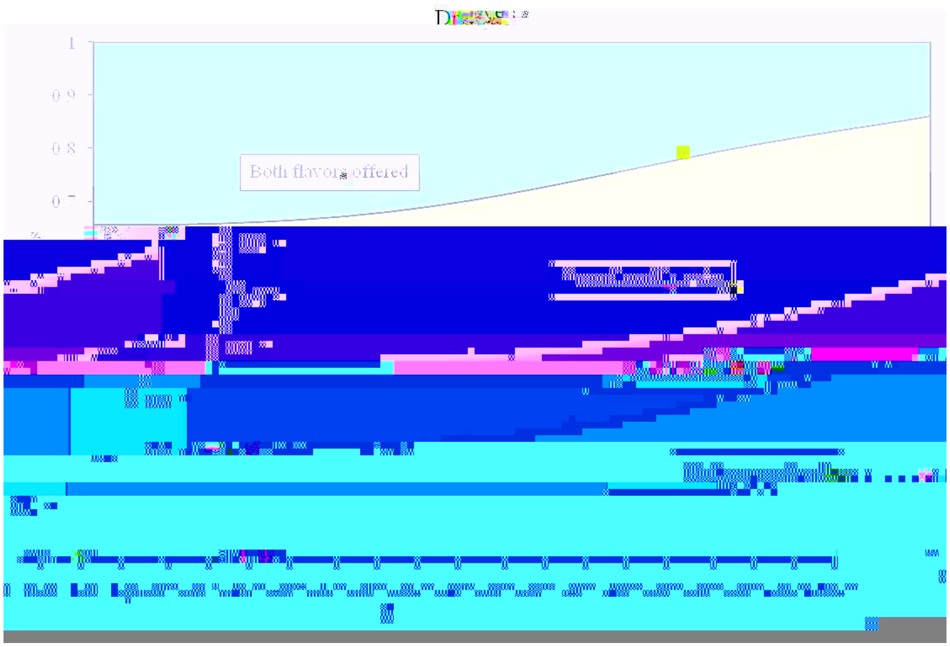

Figure 6: Assortment probabilities as a function of Breyers' degree of vertical di®erentiation.