Channel Responses to Brand Introductions: An Empirical Investigation

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August, 2007

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First version: July 2003
This version: August 2007

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Abstract:

We investigate the effect of competitive entry on manufacturer and retailer pricing behavior. Since the observed price changes can be due to entry-induced changes in a) demand conditions or b) costs, c) manufacturer’s competitive behavior, or d) retailer’s competitive behavior, a robust empirical model should be able to parse out these four sources of price changes. In order to understand realistic and managerially relevant responses to entry/brand introduction, we model manufacturer and retailer pricing as an outcome of maximizing a combination of shares and profits. This inclusion of shares in the objective function enables us to isolate the impact on prices of the four effects. Furthermore, our formulation of the objective function enables us to parsimoniously capture the full range of competitive behavior from very competitive to collusive outcomes. This formulation builds on well-established theoretical literature (including the strategic incentive design and entry literatures), anti-trust evidence and managerial practice the notion that firms’ competitive conduct manifests itself as maximizing not just pure profits but a weighted combination of profits and market shares or sales. As a result, we are able to address the following questions: (1) how do manufacturers change competitive pricing conduct as entry happens? Do some of them price to protect their market shares? Are there any patterns in this behavior in terms of weaker/stronger brands and are these patterns consistent with theoretical predictions? (2) what is the retailer’s pricing objective and conduct for each brand? Does this change with entry and in what manner? (3) how does channel power as measured by profit percentages for manufacturer versus retailer change as a result of these brand introductions, and the accompanying changes in competitive conduct? (4) how do these changes in manufacturer and retailer behavior and their power depend on the type of brand introduction i.e. if it is a de novo brand introduction versus a line extension of an established brand?

Our empirical investigation is based on the toothpaste category for the time period January 1993-February 1995. In this period, the category saw three brand introductions in two rounds of entry. We find that incumbent manufacturers’ response to brand introductions is a function of the entrant manufacturer’s brand introduction stance as well as the threat posed by incumbents. For example, the de novo entrant chooses a non-aggressive brand introduction stance. In response to this brand introduction, incumbent manufacturers price to preserve their market share, and therefore exhibit an aggressive pricing response. On the other hand, line extensions of existing brands enter more aggressively and are, in turn, accommodated more softly by other incumbent manufacturers. We find that the retailer’s response to entry is predominantly similar to that of the manufacturers’. When manufacturers respond to brand extensions aggressively by resorting to price cuts, retailers’ share of the total channel profits increases; the reverse is true for a soft accommodation of entry. Contrary to what one might expect, the entrant brand is not necessarily disadvantaged relative to incumbent brands in terms of channel profit share. Entrants who can generate good demand pull and who have a soft entry stance can expect more favorable accommodation from retailers and other manufacturers.

Key works: channels pricing, channels competitive conduct, brand introductions, profit and sales maximization
1. Introduction

The entry of a new brand can result in significant changes in competitive strategies in an industry. In this paper, we focus on an aspect of entry that has received limited attention in the literature - how firms respond to entry in their industry in the presence of channel partners who might not share the same objectives. In this connection, we investigate three main issues: a) how pricing conduct of manufacturers changes with entry, b) how competitive conduct of retailer changes with entry c) whether entry alters channel power as captured by percentage of channel profits for a manufacturer versus the retailer. To answer these questions, we need to understand the source of changes in the wholesale and retail prices before and after entry. For example, if we observe a significant drop in the wholesale price of an incumbent, we might infer an aggressive response to entry. On the other hand, if the wholesale price remains unchanged, but the retail price changes, we might infer a change in the retailer’s pricing strategy.

However, these inferences based on observed prices might be inappropriate because such price changes might be a consequence of four different factors. First, as a consequence of competitive entry, consumer preferences might change, and firms adjust their prices to these changes. For example, consider a situation when the entrant’s product closely resembles the incumbent. Since the customers of the incumbent now have a close substitute for their current product, we would expect its market demand to exhibit higher price elasticity after the new product introduction. As a result, the incumbent’s equilibrium profit margins (and possibly, the equilibrium price) will be lower after the new product introduction. We call this the demand effect. Second, the marginal cost of the product might change with entry. This might be due to changes in the prices of inputs, which might be related or unrelated to entry. This is likely to change equilibrium prices. We call this the cost effect. Third, the manufacturers might modify their competitive conduct in response to entry. For example, an incumbent may resort to significant price reductions in order to make the market less attractive to the new entrant. We call this the manufacturer conduct effect. Finally, the retailer might change her competitive behavior with manufacturers in response to new product introductions, resulting in changing retailer prices. We call this the retailer conduct effect. In order to understand changes in manufacturer and retailer conduct, we need to isolate the last two effects from observed price changes.
We build a model of channels pricing that accounts for each of these four effects; we estimate the model for both before and after entry to measure changes in these effects before and after entry. The channel players include multiple manufacturers and a single retailer. Each player chooses prices in a changing competitive environment. We do not impose a single competitive behavior in our model (e.g. Bertrand-Nash pricing) because doing so implies only demand and cost changes drive price changes. Rather, we measure deviations from Bertrand-Nash pricing in a parsimonious and restriction-free manner by modeling manufacturers and the retailer as maximizing a combination of profit and share. This formulation of the objective function is based on well-established theoretical literature (including the strategic incentive design and entry literatures), anti-trust evidence and managerial practice. This enables us to do two things. First, we are able to separate out whether each player’s responses to entry are rooted in demand and cost changes or were driven by strategic considerations outside of these two changes. Second, we measure the impact of these changes in competitive behavior on variable profits and share of variable channel profits for players.

This paper straddles two streams of literature. The first stream examines how incumbent response varies with entrant characteristics. The Defender model proposed by Hauser and Shugan (1983) marks the start of a rich stream of literature on the optimal marketing mix response of an incumbent to entry. The literature in this stream of has documented several characteristics that influence competitive behavior in response to entry. Some of these are the existence of a multi-market contact between entrants and incumbents (Bernheim and Whinston, 1990; Shankar, 1999), the quality level of the entrant (Shankar, 1997), size and resources available to the entrant (Kuester et al. 1999), as well as market characteristics such as the growth rate (Shankar, 1999). The second stream of relevant literature is the growing literature in empirical modeling of channels pricing behavior (e.g. Besanko et al. 1998, Kadiyali et al. (2000), Sudhir (2001), Villas-Boas and Zhao 2001, Berto-Villas Boas 2007, Chintagunta et al. (2002)).1 We expand on this literature by building a fully flexible model of channel competitive behavior.

In this paper, we build on the two streams of literature mentioned above. We perform our empirical investigation in the toothpaste category in the time period January 1993 through February 1995. This period was marked by two sets of brand introductions. Hence, we examine

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1 There is, of course, a rich history of theoretical papers in this area. Some of these classic papers include Choi 1991, Jeuland and Shugan 1983, and McGuire and Staelin 1983.
three slices of competitive history in the toothpaste category - period 1, the initial period, period 2 after the first brand introduction, and period 3 after the second (set of two) brand introduction(s). An interesting feature of these new product introductions is that they differ in terms of the nature of products introduced as well as the characteristics of the firms introducing these products. For example, while the first instance of entry is that of a de novo brand introduction, the second is a line-extension of existing incumbents. Hence, the data provide an interesting laboratory to study the differences between these two settings.

To anticipate the results, we find that there are significant changes in the demand-side as a result of entry. This implies that inferring changes in manufacturer and retailer conduct based solely on changes in the wholesale and retail prices might be erroneous. There are also changes in channel competitive interactions change with entry. We find that incumbent response to brand introductions is more aggressive for a de novo brand introduction than other incumbent’s brand introduction via product line extension. The de novo entrant’s brand introduction strategy is softer, possibly fearing aggressive response and lacking the resources to fight back. Based on the change in direction of pricing conduct in response to competitive entry, there appears to be a high degree of commonality between the manufacturers and the retailer. We also find that the retailer’s share of total channel profits increase when brand introduction is accommodated aggressively. The reverse is true when brand introduction is accommodated softly. Interestingly, entrants who can generate good demand pull and who have a soft entry stance can expect more favorable accommodation from retailers and other manufacturers.

The rest of the paper is organized as follows. In Section 2, we provide more details on the toothpaste category and the data. In Section 3, we discuss our model. Section 4 has results, and we conclude in section 5.

2. The Toothpaste Category: Overview and Data

2.1. Overview of the Toothpaste Category

Starting 1988, the toothpaste category saw the introduction of two new brands of toothpaste – Arm & Hammer and Mentadent. Also, there were two significant innovations during this period. The first significant innovation was the addition of baking soda to toothpaste (Arm & Hammer in 1988). Arm & Hammer was able to obtain a market share of 8%, despite its price premium, and despite the dominance of giants such as Procter and Gamble and Colgate.
Palmolive (Advertising Age 1992, Brandweek 1993). Colgate and Proctor and Gamble’s Crest introduced their baking soda toothpaste in January 1992 and January 1993, respectively. Aquafresh was the last to introduce the same in July 1994.

The second significant change in the product formulation was the introduction of toothpaste with baking soda and peroxide by Mentadent in September 1993. Despite the significantly high price at which it was introduced, Mentadent was an instant success. Then Arm & Hammer retaliated with its own version in July 1994, followed by Colgate and Crest.

These significant new product introductions make toothpaste a good category to study entry effects in a channels context. As noted in the introduction, we break our data period of January 1993 to February 1995 into three periods. The first is prior to any entry. The second is after the introduction of new product by a new entrant, Mentadent baking soda and peroxide. The third after the almost simultaneous introductions of line extensions by two incumbents, i.e., Arm & Hammer baking soda and peroxide and Aquafresh baking soda toothpastes.

2.2. Data Description

We perform our analysis using the Dominick’s Finer Foods data, which consist of weekly sales figures, retail and wholesale prices and the presence of promotions (coupons, bulk buy or a special sale) by UPC and daily store traffic for stores operated by Dominick’s in the Chicago area.

During the initial period, we restrict our analysis to six brands – Arm & Hammer Baking Soda formulation (A&H-B), Aquafresh (Aqua), Colgate (Colg), Colgate Baking Soda (Colg-B), Crest (Crst), and Crest Baking Soda (Crst-B). Together these brands account for 81% of the total category sales. We present the descriptive statistics corresponding to these brands in Table 1. In our analysis, the data corresponding to this period span 31 weeks from January 1993 through August 1993.

--------------Insert Table 1 here--------------

The second period has seven brands (including the new entrant) that have 78% of the total category sales. The data corresponding to this period span 44 weeks from September 1993 through July 1994. The four large brands of Colgate and Crest saw their combined share fall to about 74%. Their response to brand introduction was lowering their wholesale prices on the large brands Colg and Crst, which appear to be passed on by the retailer in terms of lower retail prices.
In the third period, there are the two line-extensions. The nine brands shown account for 80% of the total sales in this category. The data corresponding to this period span 30 weeks from July 1994 through February 1995. Note that these line-extensions come in at a lower price than Ment-B+P’s entry price. The four brands of the largest two competitors gain share somewhat to about 75.8%. Overall retail and wholesale prices appear lower.

To understand more details of what these price and share movements say about changes in underlying demand, or cost, or competitive conduct, we need to estimate an equilibrium model of channel pricing.

3. Model and Estimation

3.1 Model

We begin this section with a description of the demand model, followed by descriptions of the manufacturer and retailer pricing models.

3.1.1: Demand

We use a mixed logit model (Berry, 1994, Berry et al. 1995, Nevo 2000, Nevo 2001). For notational convenience, we suppress the subscript for the regime in the subsequent presentation. The indirect utility for consumer i from brand j (j = 1, 2, ..., J) in time period t (t = 1, 2, ..., T), U_{ijt} is given by the following expression.

\[
U_{ijt} = \alpha_i + \beta_i p_{jt} + \gamma_i X_{jt} + \mu_{jt} + e_{ijt}
\]  

\(\alpha_i\) is consumer i’s intrinsic brand preference for brand j, \(\beta_i\) is consumer i’s price sensitivity parameter, \(p_{jt}\) is brand j’s price at time t, \(\gamma_i\) is consumer i’s sensitivity to other marketing activities in time t, \(X_{jt}\). The term \(e_{ijt}\) in the above equation captures the unobserved component of consumer i’s utility for brand j at time t, \(\mu_{jt}\) captures the brand and time specific factors that are common across consumers that could influence consumer i’s utility for brand j in period t. For example, this term includes the effect of availability of the brands to the consumer, the shelf space or shelf location assigned to the brands, or assortment length/depth, etc. These factors are important to consumer choice decisions. Importantly, these factors are observable both to the consumers and the retailers/manufactures but not observable to the researcher. These factors are referred to as “demand shocks” or “unobserved attributes” of the brands. These factors could be correlated with the marketing activities of firms (prices in our model) that are included in the
utility function above in $p_{jt}$ and $X_{jt}$, thus requiring correcting for econometric endogeneity of price in the demand function (Berry 1994) (more details below).

To fully specify the model, we allow consumers to not purchase from the category with an “outside good” alternative represented by $j = 0$, whose utility is given as follows (see section 3.2 for precisely how this outside good is calculated):

$$U_{i0t} = \tilde{\alpha}_{i0} + e_{i0t}$$  \hspace{1cm} (2)

The unobserved utility components, $e_{ijt}$ are assumed to be i.i.d. type I extreme value distributed across consumers, brands and time periods. This yields the familiar logit brand choice model for the market share of brand brand $j$ at time $t$, $S_{jt}$,

$$S_{jt} = \int \frac{\exp(\alpha_j + \beta p_{jt} + \gamma X_{jt} + \mu_{jt} + \Delta \alpha_{ij} + \Delta \beta_{ij} p_{jt})}{\sum_{j=1}^{\infty} \exp(\alpha_j + \beta p_{jt} + \gamma X_{jt} + \mu_{jt} + \Delta \alpha_{ij} + \Delta \beta_{ij} p_{jt})} dF(\theta).$$  \hspace{1cm} (3)

In the above expression, note that we have expressed the household $i$’s preference coefficients as a sum of the market level mean and the deviation in household $i$’s preference from this mean preference. Specifically, $\alpha_{ij} = \alpha_j + \Delta \alpha_{ij}$ and $\beta_i = \beta + \Delta \beta_i$. The term $F(\theta)$ denotes the distribution function of the heterogeneity across consumers. Further details regarding the model can be found in Berry, Levinsohn, and Pakes (1995).

3.1.2 Price setting behavior:

The starting point for measurement of competition is the following: consider a firm $j$ maximizing its profits $\Pi$ for time period $t$, by choosing prices $p$, and facing marginal costs $c$, a market size $M_t$, and its share of the market $s$. Any change in demand or cost is captured in the price setting behavior given this pricing model is estimated separate for each period.

$$\Pi_{jt} = (p_{jt} - c_{jt}) s_{jt} M_t$$

The first-order condition for a manufacturer choosing prices under Bertrand-Nash assumptions is as follows:

$$(p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{jt}} * M_t + s_{jt} M_t = 0 \hspace{0.5cm} or \hspace{0.5cm} p_{jt} - c_{jt} = -\frac{s_{jt}}{\frac{\partial s_{jt}}{\partial p_{jt}}}.$$
The above pricing equation expresses price as a sum of the marginal cost and the equilibrium margins. Hence, under the Bertrand pricing scheme, any change in price post entry is explained solely by the cost and demand effects. Porter (1983), generalized the above pricing equation to capture a wide variety of competitive interactions by introducing an additional parameter $\theta$ as follows,

$$(p_\mu - c_\mu) \frac{\partial s_\mu}{\partial p_\mu} (1 + \theta) M_\tau + s_\mu M_\tau = 0 \text{ or } p_\mu - c_\mu = -\frac{s_\mu}{\partial p_\mu} (1 + \theta)$$

If $\theta$ is zero in the above equation, this equation is identical to the previous equation for Bertrand-Nash pricing. A positive value of $\theta$ gives a mark-up larger than Bertrand-Nash (given own share-price effect is negative), a negative value of $\theta$ leads to mark-ups smaller than Bertrand-Nash (Porter, 1984).

Given the above framework for measuring competition, researchers have adopted three broad ways of measuring competition. The first is imposing assuming a particular value of $\theta$ in the data (e.g. Besanko et al. 1998, Sudhir 2001; Chintagunta 2002). This approach implies that all observed price changes must come from either demand or cost changes. Therefore, this approach is not appropriate for our purposes.

The second approach is to measure a subset of possible games among channel member. For example, BertoVillas-Boas (2007) measures a menu of vertical interaction games among channel members to identify the one that best describes the data. Some of these games can be mapped in to specific values of $\theta$. While this approach can isolate the changes in the nature of competitive interaction over time, it is cumbersome to estimate a menu of possible interactions under three different regimes. It is also possible that the estimation of $\theta$ from data might yield a value not easily mapped in to any closed form known game (like leader-follower, etc.).

The final approach is of Kadiyali et al. (2000), who estimate for each manufacturer-retailer and manufacturer-manufacturer pair a competitive conduct parameter $\theta$ that measures deviations from Bertrand-Nash pricing. While this approach is better-suited for our application of measuring changes in competition, it is very data-intensive. For example, in the context of our application wherein we have seven brands, we need to estimate 42 parameters for pairwise interactions between manufacturers. Additionally, if we were to model the channel interaction between the each brand and the retailer, we need to estimate seven more parameters. Also,
parameterizing these conduct parameters as functions of observables imposes further constraints in the estimation. Therefore, we build on the Kadiyali et al. (2000) approach, but we measure for any player (manufacturer or retailer) the net effect of interactions with all players (rather than a pair-wise measure for each dyad of players). More details are provided below.

(a) Manufacturer Pricing

We consider the following objective function for manufacturer $m$:

$$\Pi_{m}^{M} = \sum_{j \in B_{m}} (w_{jt} - c_{jt}) s_{jt} M_{j} + \gamma_{j} s_{jt},$$

where $\Pi_{m}^{M}$ is the objective function of manufacturer $m$, $m = 1, 2, \ldots M$, $B_{m}$ is the set of brands manufactured by the manufacturer, $w_{jt}$ is the wholesale price set by manufacturer $m$ for brand $j$ at time $t$, $c_{jt}$ is the marginal cost of brand $j$ at time $t$, and $\gamma_{j}$ is the weight placed by the manufacturer on the share of brand $j$. We expect that the weights placed on market shares to vary by manufacturer, and the data will reveal whether or not this is true.2

There is widespread support in the literature for this enhanced objective function. Consider the literature on strategic incentive design, which explores competitive equilibrium in a super-game theoretic framework. It suggests that a firm that maximizes a combination of profits and market shares or sales might send a signal of aggressive competitive intent to a rival and therefore promote a leader-follower equilibrium rather than Bertrand-Nash pricing (Fershtman, 1985, Fershtman and Judd 1987, Skilvas 1987).3 Additionally, Bell and Carpenter (1992) and Gruca et al. (2002) find that incumbent firms anchor on preserving pre-entry levels of market shares4. Gruca et al. (2002) study the retail coffee market and find support for a model for

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2 Note that the units of measurement are different across the two parts of the objective function of profits and shares. That is, pure profits are in dollars, whereas shares are in percentage. Hence, we cannot model the weights on these two parts as summing up to 1 or restrict them in any other way. However, we will be able to compare the contribution of each of these parts to total profits (see Section 4 on the empirical results) and hence be able to comment on the relative importance of each of these.

3 See also Balasubramanian and Bhardwaj (2004) who demonstrate that managerial compensation based on a combination of profits and market shares or sales can increases total channels profits. They also show that under certain conditions, total channel profits are highest when managers at both the manufacturer and retailer are compensated in this manner, given all players recognize the possibility of price wars should any one player in the channel decide to reduce price to capture more shares. This leads to more collusive channels outcomes.

4 Even in a non-entry context, firms might have various reasons to emphasize market share. See McGuire et al. 1962, Osborne 1964, Ciscel 1974, Cox and Shauger 1973, Smyth et al. 1975, Diamantopoulos and Mathews 1994. These authors' arguments include managers' desire to maintain market shares for stock-market or prestige reasons, as well as to ensure strong bargaining positions in their industries, the inherent ability to understand market shares in clearer terms than profits which are harder to measure, etc.
multiple objectives of market share preservation and profit maximization. Placing a larger positive weight on shares post-entry implies aggressive pricing and signals to the entrant an aggressive incumbent stance.

There are also reasons for firms to place a negative weight on shares in an entry context. First, firms might adopt a focused or niche differentiation strategy (Porter, 1979) i.e., where firms care about maintaining high mark-ups obtained from catering to a small proportion of the market. This need to differentiate from competitors might increase with entry. Second, a negative weight on shares indicates an accommodating stance.

Solving the first order conditions, we obtain the following pricing rule for the manufacturers:

\[
\frac{w_t - c_t + \gamma}{M_t} = -\left( \frac{\partial s_t}{\partial p_t} \cdot * \Theta \right)^{-1}(s_t), \text{ where}
\]

\[
w_t = \{w_{1t}, w_{2t}, \ldots, w_{Jt}\}, \text{ the vector of wholesale prices of the J brands}
\]

\[
c_t = \{c_{1t}, c_{2t}, \ldots, c_{Jt}\}, \text{ the vector of marginal costs of the J brands}
\]

\[
s_t = \{s_{1t}, s_{2t}, \ldots, s_{Jt}\}, \text{ the vector of market shares of the J brands}
\]

\[
\Theta = \text{manufacturer ownership matrix of dimension J x J such that the element } \Theta(j,k)
\]
equals one when both brands j and k are produced by the same manufacturer and zero otherwise, and

\[
\frac{\partial s_t}{\partial p_t} \cdot * \Theta \text{ corresponds to the element by element multiplication of the two matrices.}
\]

Since the wholesale price of each brand is written as a function of its marginal cost, the implied equilibrium price-cost margin, \(-\left( \frac{\partial s_t}{\partial p_t} \cdot * \Theta \right)^{-1}(s_t)\), and the manufacturer conduct effect, \(\frac{\gamma}{M_t}\). Given our estimates of demand and supply equations before and after entry, we can measure how these values change with entry.

Similar to Berto Villas-Boas (2002), we use an exponential specification for the marginal cost to ensure that these estimates are positive.\(^5\) Thus, the marginal costs can be expressed as

\(^5\) The alternative specification is to make these costs functions of factor prices (e.g., labor, capital and other ingredients). This alternative specification can sometimes lead to odd signs in estimation (e.g., negative for...
\[ c_{jt} = \exp(C_{jt}) + \varpi_{jt}, \]  

where \( C_{jt} \) is (logarithm of) the estimated marginal cost for brand \( j \). This cost parameter can be interpreted as the average cost for the estimated time period, or as the time invariant marginal cost through the period.\(^6\) The term \( \varpi_{jt} \) captures the component of marginal cost that is unobserved by the researcher but is observed by the firm. Examples of such unobserved (time-varying) cost shocks could include changes in the cost of ingredients that go into making toothpaste.

A necessary condition for the identification of the weights placed on market share is that the market size varies over time.\(^7\) This can be accomplished by setting the market size as a function of store traffic. We create a cumulative store traffic variable (CT) as in Chintagunta (2002), which is an exponentially smoothed version of the store traffic and use this as an assessment of the expected store traffic. Formally, the cumulative store traffic can be expressed as:

\[ CT_t = \tau T_{t-1} + (1-\tau)CT_{t-1}, \quad 0 \leq \tau \leq 1, \]  

where \( T_{t-1} \) is the store traffic and \( CT_{t-1} \) is the cumulative store traffic, both at time \( t-1 \). A value of \( \tau \) close to 1 would imply that the assessment of store traffic would be driven primarily by the store traffic during the previous week, whereas the opposite is true when \( \tau \) is close to zero.\(^8\)

Note that by including store traffic, we are able to control for retail competition effects, albeit indirectly. We discuss this shortly.

(b) Retailer Pricing

We model the following retailer objective function:

\[ \Pi^R_t = \sum_{j=1}^{J} \left( p_{jt} - w_j \right) s_j \lambda_j M_t + \lambda_j s_{jt}, \]  

ingredients) and sometimes even insignificant results. Hence the choice of fixed effect cost functions and the exponential specification.

\(^6\) It is possible that there are some learning economies, most likely for the \textit{de novo} entrant (the other brands introducing line-extensions have been in the category and are imitating existing products. So it appears less likely that they have learning economies). However, in our estimation we find for the de novo entrant that there is no significant drop in marginal cost across periods 2 and 3 (see table 4, last row for Mentadent); if anything there is a minor increase. (Note that given we do not have a “period 4”, we cannot see if the other manufacturers introducing line extensions see a decrease in marginal costs after entry). Given this, we abstract from the issue of learning economies.

\(^7\) If the market size did not vary over time, the coefficient would get absorbed in the intercept term. Thus, we would not be able to identify the marginal cost separately from this weight.

\(^8\) Based on Chintagunta (2002), we fix the value of \( \tau = 0.6 \) in our estimation.
where, \( p_jt \) and \( w_jt \) are the retail and wholesale prices of brand \( j \) at time \( t \), \( s_jt \) is the market share of brand \( j \) at time \( t \), and \( M_t \) is the potential size of the market at time \( t \). \(^9\) The parameters \( \lambda_{jt} \), \( j=1, 2, \ldots J \) represent the weight placed by the retailer on the share of brand \( j \). In other words, the last term in Equation (8), \( \lambda_j s_jt \), corresponds to the importance of the retailer places on the share of brand \( j \) in his objective function.\(^10\) Note that a positive (negative) weight on the share of any brand leads to lower (higher) retail prices, and hence lower retailer profit margins than under Bertrand-Nash pricing.

There are several reasons why retailers might choose the above enhanced objective function rather than pure profit maximization. First, as mentioned above, such an enhanced objective function captures the super-game theoretic competitive interactions in channels better than a simple objective of profit maximization. Second, retailer might have objectives like store-traffic generation that are consistent with increasing the market shares of some brands that can draw traffic (see Chen et al. (1999), Urbany et al. (2000) and Srinivasan et al. (2003) for empirical evidence).

Finally, to confirm our intuition, we spoke to a retail expert who said:

“…Maximizing sales and market share" may actually be a major motivator. There is a strong tradition in retailing to boast about high sales (and gross margin too). There is strong machismo attached to sales or market share leaders. A store manager, a category manager and even the VP of marketing (and sales), rarely has any understanding of what economists (or even accountants) would call profits… Thus, they are actually being rational in maximizing what they can see, understand and often what they are provided incentives for: sales (and at higher levels, market share)”

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\(^9\) Benchmarking our specification of the retailer’s objective function with existing literature, Meza and Sudhir (2005) examine if retailers choose to favor some national brands over others, especially relative to store brands. Therefore, they model the objective function of the retail channel as the more commonly accepted category profit maximization plus another term that places an extra weight on profits coming from private label brand (or negative weights on national brand profits. Therefore, our retailer objective function where extra profits come from emphasizing market share, and including vertical strategic interactions with manufacturers with explicit links to a general model of competition in channels, can be seen as a generalization of Sudhir and Meza (2005)

\(^10\) See also Meza and Sudhir (2005). They examine if retailers “favor” some national brands over others, especially over store brands, in terms of placing extra weight on profits coming from these brands. Our interpretation of weights on shares can be seen as a generalization of their intuition, and adding a vertical strategic interaction perspective to the issue.
Turning now to the empirical implementation of retailer pricing behavior, note that our characterization of the objective function in equation (8) is based on a single retailer, i.e. we make the implicit assumption that retail competition does not affect retailer price setting. While this assumption may seem restrictive, there is very limited evidence of direct retail competition in any one category (Slade, 1995). Therefore, examining the problem in the context of a single retailer appears reasonable when examining any single category. Reconciling this with our previous discussion of traffic generation motives to emphasize share of a particular brand, there is clearly competition among retailers across categories or baskets of goods given researchers have found that basket prices matter to consumer choice of retail stores (Bell et al. (1998) and Bell and Lattin (1998)). Therefore, a weight on the shares of a brand accomplishes two goals. First, it captures the vertical strategic interactions with manufacturers. Second, it allows for a store-traffic measure to capture possible cross-category retailer competitive effects. Recall that market size is defined by store traffic (Equation 7) and therefore includes in it another measure of cross-category retail competitive effects.

Solving the first order conditions with respect to the retail price would imply the following optimal pricing rule for the retailer

\[
p_t - w_t + \lambda = -\left(\frac{\partial s_t}{\partial p_t}\right)^{-1}(s_t), \text{ where}\]

\[
\begin{align*}
p_t &= \text{vector of the retail prices of the } J \text{ brands during period } t, \\
w_t &= \text{vector of wholesale prices of the } J \text{ brands during period } t, \\
\lambda &= \text{vector of the weights placed by the retailer on the market share of the } j \text{ brands,} \\
s_t &= \text{the market shares of the } j \text{ brands, and} \\
\frac{\partial s_t}{\partial p_t} &= J \times J \text{ matrix representing the derivatives of the } j \text{ brands with respect to their prices during period } t.
\end{align*}
\]
Since our data have information on the wholesale prices, the term $\frac{\lambda}{M_t}$ from the retail pricing equations for the brands gives us the weights placed on brand shares.\footnote{If wholesale prices were not known, identification of weights on shares would not be possible without parameterizing these weights as being functions of other observables (e.g. change in shares in the last time period etc.). The latter approach seems ad-hoc, in the absence of any theory justifying such parameterization. Hence the choice of Dominick’s data set, as we discuss in section 3.1, where these wholesale prices are observable. This is similar to Meza and Sudhir (2005).} With pure profit maximization, the vector $\lambda = 0$.

Equation (9) implies that the observed retail price is a sum of three components – the wholesale price, implied equilibrium retailer margin, $-\left(\frac{\partial s_t}{\partial p_t}\right)^{-1}(s_t)$, and the channel interaction effect, $-\frac{\lambda}{M_t}$. We use the estimated differences between these terms before and after entry to infer the extent to which the change in retail price is attributable to changes in wholesale price, retailer demand effect, and the manufacturer competitive conduct. Hence, while we use the change in wholesale prices as a result of entry to infer the competitive conduct effect, we use the retail margin $(p_t - w_t)$ to isolate the channel interaction effect.

3.2. Operationalization of Variables

3.2.1 Marketing Mix Variables

We operationalize the retail price as the weighted (by unit sales) average price per oz. of all the UPCs in the brand, averaged at the chain level.\footnote{The UPCs in each product variant were priced and promoted similarly as evidenced by the high correlation in their prices – greater than 0.8. Hence, it appears that the UPCs within a product variant were homogenous.} Following Chintagunta (2002), we define the sales promotion variable as the proportion of UPCs in the product variant that were available on a sales promotion that week. In the supply side, we operationalize as the weighted average wholesale price similar to retail price.\footnote{A comment about the use of the wholesale price information from the Dominick’s database is in order. As noted in the University of Chicago’s website for the Dominick’s database, the wholesale price (inferred from the retail profit margin provided in the Dominick’s database) reflects the average acquisition cost (AAC) of items in the inventory. Given that the AAC is a weighted average of the price that the retailer paid in a given week and the average acquisition cost of the previous week, it can potentially have the problem of sluggish adjustment (Peltzman 2000). Hence, if Dominick’s holds large inventories of the product purchased at regular wholesale prices, then any impact of trade promotions (which imply lower wholesale prices) will only be reflected gradually as the regular priced inventory is depleted. Hence, AAC is unlikely to be an accurate indicator of the wholesale price. However, as Besanko, Dube, and Gupta (2005) note, there are two mitigating factors that counteract this sluggish adjustment implying that any change in the wholesale price is quickly reflected in the AAC. First, Chevalier et al. (2003) note that DFF’s optimal inventory management typically results in trade promotions (lower wholesale prices) reflected in}
3.2.2. Outside Alternative

The estimation of the demand-side model requires the definition of an outside or no-purchase alternative. Based on information from the IRI *Marketing Fact Book*, we assume that each household consumes 4 oz. of toothpaste every week and then multiply the store traffic in a week by the weekly consumption rate to define the market size. We then subtract the sales of the brands under consideration to compute the “sales” of the outside alternative. The respective shares are then computed from the sales of the brands and the market size as defined above. This approach is similar to that used by Chintagunta (2002).

3.2.3. Instrumental Variables

In the demand model, we allow for endogeneity of price through the use of instrumental variables. Potential candidates for instruments include product characteristics (Berry, Levinsohn, and Pakes 1995), raw materials costs (Besanko, Gupta, and Jain 1998), and prices from other regions (Nevo 2001) amongst others. After considering and testing several groups of available instruments, we selected the producer price indices for the toothpaste category because they reflect the manufacturers’ cost of producing toothpaste (see Chintagunta, Bonfrer, and Song 2002). We interact these instruments with brand dummies to generate brand specific instruments (Nevo 2001). We also include other variables that are assumed to be exogenous in the estimation.

On the supply side, retail price-cost margins depend on the demand substitution patterns retailers face and manufacturer price-cost margins depend on the derived demand substitution patterns. These, in turn, depend on all the retail and wholesale prices, which will be correlated with the contemporaneous unobserved determinants of these prices in the supply side errors (Berto Villas-Boas 2002). In order to account for this endogeneity, we use lagged price cost margins as well as other exogenous variables discussed above as instruments.

3.3: Estimation

We use a two-stage estimation procedure to obtain the parameters of the proposed model (Newey and McFadden, 1994). First we estimate the parameters of the aggregate demand function, explicitly accounting for endogeneity in price by using the contraction mapping procedure of Berry et al. (1995). Interested readers are referred to Nevo (2001) for details.
regarding the estimation. Once the demand parameters are estimated from the steps above, we then estimate the supply side by simultaneously estimating the retailer’s first-order conditions for retail price setting and manufacturer’s first-order condition for wholesale price setting, taking as given the demand parameter estimates.

4. Results and discussion

4.1 Demand estimates

We present the estimates from the demand model in Table 2. As expected the price coefficient is negative; promotions have a significant positive effect on the sales of the brands during all the three periods. We present the own-price elasticities for each time period in Table 3 (cross-price elasticities have been excluded from here to keep the presentation simple). The magnitude of a brand’s price elasticity will have a bearing on the implied equilibrium profit margins for the brand and hence on the demand effect.

------------------------Insert Tables 2, 3 here------------------------

4.2: Manufacturers’ Competitive Conduct

We present the estimates from the manufacturer pricing model in Table 4. Casual observation as well as econometric tests reveal that marginal costs are stable across time periods for any brand. Hence it is unlikely that the observed changes in prices are due to changes in marginal cost. All changes in competitive conduct as measured by changes in weights on shares are significant.

------------------------Insert Tables 4, 5 here------------------------

In the first time period, we find that for Colgate’s product, Colg has aggressive pricing to protect its share, Colg-B has soft pricing conduct. The reverse is true for Crest’s product line- Crst prices non-aggressively, and aggressive pricing conduct to protect shares for Crst-B.\textsuperscript{14} This mirror image in objectives is consistent with tacit collusion maintenance where firms with product line choose one product as a leader for competitor’s follower product, the other as a follower for competitor’s leader product (see Kadiyali et al. (1996) for a parallel result in the detergent market). A&H-B is a small player with a high-priced high-elasticity product, and it prices softer than Bertrand-Nash, a strategy to be the premium brand in the market. Aqua sets its

\textsuperscript{14} Given we are not estimating a menu of alternative games, we are unable to precisely say to which game any measured level of competition corresponds; we can only benchmark against Bertrand-Nash.
prices based on the objective of pure profit maximization. Note that similar to A&H-B, Aqua is also a relatively small share brand with high price elasticity.\(^{15}\)

In the second period, Ment-B+P enters at a high price point.\(^{16}\) Its entry strategy is softer than Bertrand pricing (as indicated by the negative weight on shares) or a “puppy dog” ploy (Fudenberg and Tirole, 1983). A&H-B switches to the aggressive pricing conduct, consistent with A&H-B seeing Ment-B+P as a threat to its share, or exploiting Ment-B+P’s higher price/higher elasticity to reduce its own price somewhat to capture market share. Aqua switches from pure profit maximization to aggressive pricing. Therefore, Aqua’s response indicates that despite the higher price of Ment-B+P, it is still vulnerable because of its small market share.

For Colgate, although there is no directional change in these parameters, as seen in Table 6, there is a significant increase in the weight placed by Colg on its share, while the opposite is true for Colg-B. Crest does aggressive pricing to protect share of both its brands, switching its main brand Crst to aggressive pricing, and increasing the weight placed on shares of Crst-B. Therefore, all the incumbents with the exception of Colg-B respond to the entry of Ment-B+P by pricing aggressively (i.e. a “top dog” for the big brands, and “lean and hungry” for the smaller brands; see Fudenberg and Tirole 1983).

In the third time period after the brand introduction of A&H-B+P and Aqua-B, we see that manufacturer behavior changes once more. Consider first the behavior of the entrants. Unlike Ment-B+P’s adoption of a soft pricing conduct, A&H and Aquafresh adopt a more aggressive brand introduction strategy or a “lean and hungry” brand introduction stance (Fudenberg and Tirole, 1983). A&H’s new brand A&H-B+P’s pricing does not deviate significantly from profit maximization or Bertrand pricing, and its older brand A&H-B continues with aggressive pricing to protect share. Aquafresh’s new Aqua-B brand also has aggressive pricing.

The incumbent response to these two brand introductions is as follows. Ment-B+P, which was previously pricing soft, now switches to aggressive pricing to protect share possibly due to the lower priced entries that threaten it further. Additionally, Ment-B+P might perceive a direct threat from A&H-B+P, which threatens to dilute its unique positioning as the only brand offering

\(^{15}\) While we are interpreting the weights on shares as if period 1 is the initial period, recall that Crest Baking Soda was introduced prior to this period, so period 1 is itself a competitive response period to that line-extension.

\(^{16}\) There are two components to Mentadent’s high price point. One is whether the price would have been high if the weight on shares had been zero i.e. under pure profit maximization/Bertrand-Nash pricing. The other component is how much higher the price is as a result of softer-than-Nash competitive conduct by Mentadent.
the baking soda and peroxide formulation. Colgate and Crest respond by choosing less aggressive objective functions - Colgate switches to soft pricing for both its brands (from only one in previous period 2) and Crest does the same for one of its brands (from none in previous period 2). Therefore, the large incumbents’ accommodation stance looks like a “fat cat” stance (Fudenberg and Tirole, 1983). Overall, we find that with the exception of Ment-B+P and Colg-B, all the incumbents react to the entry of these line extensions with a decrease in the weight they place on the shares of their respective brands (see Table 6 for a visual summary of this).

What explains the difference between the second and third time periods? Turning first to entry strategy, Mentadent is a de novo entrant, and therefore might not have resources to adopt an aggressive entry stance or pricing strategy. Both A&H and Aqua had presence in the market, and relationships with retailers were already in place, enabling them to adopt a more aggressive stance or pricing strategy. This is consistent with the literature (see, for example, Gatignon et al. 1990) that firms that have more resources to back new brands make more aggressive entrants.

The reasons for the contrast in incumbent response to entry- aggressive to Ment-B+P and accommodating to A&H-B+P and Aqua-B- can also be found in the literature. Consider first the difference in threats posed by these entrants. Mentadent was introducing a new feature of peroxide which ex-post ended up being a major, high-quality innovation in the category. If incumbents correctly anticipated this, the literature supports the view of aggressive responses to entrants posing larger perceived threats (Kuester et al. 1999, Shankar, 1999), especially if accommodation of this threat might encourage other potential entrants.

Another explanation for the accommodating response in the third period is that the incumbents and as well as the brands introducing line-extensions have prior contact in the market. While prior contact (or its variant, multi-market contact) can make competition more aggressive (see Porter, 1979), in our case it appears to cause mutual forbearance (Bernheim and Whinston, 1992), at least as evidenced by the large incumbent reaction. Therefore, our findings appear consistent with existing literature; the laboratory of examining different reactions to de novo brand introduction versus line-extensions provides interesting corroboration of existing theories in the literature.

Summarizing, manufacturer reaction to competitive entry is correlated with (1) the position of the player (larger versus smaller players, higher priced versus lower priced brands) (2) the nature of the changes in the competitive landscape (de novo entrant versus existing
player’s brand introduction) (3) and the pricing conduct/competitive stance chosen by the entrant. Given that our model is general enough to allow a variety of incumbent and entrant responses via the flexible competitive pricing conduct of each, we believe we are able to provide robust analysis to corroborate existing theories of entry and responses to it.

4.3: Retailer competitive conduct

In Table 6, we present the estimated weights on shares of each brand in each time period placed by the retailer. In Table 7, we decompose the observed retail margin into changes coming from channel interaction and pricing changes coming from changes in demand conditions. As Table 7 shows, like the manufacturer, the retailer’s pricing is affected both by changes in the nature of channel interactions and demand-side changes.

In the first time period, we find that the retailer resorts to aggressive pricing for the two largest brands Colg, Crst, and for Crst-B. Accommodating or soft pricing is done only for Aqua. As can be seen in Table 6, during this period, Colg, and Crst-B price aggressively to protect sales, and A&H-B and Crst price softly.

In the second time period, with the introduction of Ment-B+P, the retailer chooses Ment-B+P and A&H for soft pricing. Both of these are high-priced brands that could offer higher margins to the retailer. All other brands, including the larger ones, are priced aggressively to protect sales. An investigation of the changes in the weights placed by the retailer on the shares of the various brands reveals that between the first and the second periods (i.e., as a consequence of the entry of Ment-B+P), the retailer’s pricing is more aggressive for all brands except A&H-B. Recall that all the manufacturers except Colg-B also priced more aggressively in response to the entry of Ment-B+P.

In the third time period, which marks the introduction of A&H-B+P and Aqua-B brands, the retailer prices the new entrant, A&H-B+P softly. All other brands are priced aggressively to protect shares. Contrast this to manufacturer behavior two largest brands, Colg and Crst price softly, as well as Colg-B.

Note that the retailer exhibits more aggressive pricing that manufacturers right through the period. However, over the three time periods, the retailer’s change of pricing conduct is more in line with the manufacturers, with only 3 out of 15 changes in periods 2 and 3 being different from manufacturers’ changes. This broad similarity of pricing goals and changes in them for
reasons could be either because manufacturers use their power (as evidenced by large share of channel profits) to influence retailers to set prices that are in congruence with their (manufacturers’) own interests, or persuade them via fees and other monies. Alternatively, the retailer may have her own reasons such as retail competition (captured in a reduced-form manner in our model) to choose these pricing policies.

4.4: Changing channel power with brand introductions

We now examine the impact of entry on manufacturer and retailer profits by brand, and overall in the market in the three time period.

In Table 8, we present the weighted average retailer and manufacturer margins expressed as a percentage of the retail price of the various brands and across the three periods. These percentages indicate how the manufacturers and the retailer apportion the total channel profits amongst themselves. Hence, we can draw inferences regarding the nature of power in the channel as well as how the power shifts with new product introductions. Note first that in each period, the weighted average retailer and manufacturer margins are each quite large (no lower than about 18.4% and 35.7%) respectively, and that there are no large swings in these across the time periods.

Microeconomic theory suggests that brand introduction upstream should increase competition and therefore should have increased the rents captured by downstream players (see Perry 1987 for a survey of related literature). Consistent with economic intuition, we find that as incumbents upstream responded to de novo entrant brand introduction aggressively, retailer’s margin increases (from 18.39% to 20.57%) in moving from period 1 to period 2, and manufacturer margin diminishes (from 38.93% to 35.66%). However, in moving from period 2 to period 3, retail margin decreases (to 18.52%) and manufacturer margin increases (to 37.07%). Hence, when the manufacturers adopt an aggressive stance to brand introduction, there is a decrease in the manufacturer margins as a percentage of the total channel profits. On the other hand, when a manufacturer accommodates brand introduction, his margin as a percentage of the total channel profits increases. Therefore, upstream brand introduction per se is not always beneficial to the retailer. Taking a more detailed look within each time period, for the larger companies, Colgate and Crest (and even there not for their smaller brands all the time), retailer margins are smaller than manufacturer margins. This situation does not change despite
competitive entry. In other words, entry in this category has been insufficient to dislodge the dominance of these large manufacturers. For all other manufacturers, retail margins are healthier than manufacturer margins.

Note that the entrant does not necessarily have the lowest power relative to the retailer - Ment-B+P margins are not the lowest compared to the retailer, and neither is A&H-B, though Aqua-B is indeed disadvantaged as one might expect an entrant to be. Ment-B+P not-the-weakest hand likely comes from its high-priced brand introduction that affords the retailer more profits and still leaves room for Mentadent to make money too. Moreover, its unique baking soda and peroxide formulation helped it differentiate itself from its competitors and hence command a significant price premium in the market. Aqua-B’s disadvantage relative to the retailer likely comes from its me-too position - it was introducing baking soda feature when two of its same-sized competitors had already introduced the next generation feature (peroxide).

In sum, our analysis of channel power implies the following. First, we find that large manufacturers have greater percentage of channel profits, i.e. they have more power than retailers despite entry. Second, aggressive competition among manufacturers shifts the channel power to the retailer. Consequently, the retailer might consider encouraging de novo entrants by providing better retail terms, in order to encourage further competition upstream. Third, entrants that provide meaningful differentiation in the market or higher price are not necessarily disadvantaged in terms of profit relative to incumbent brands.

5. Conclusion

The principal objectives of this paper were to understand the impact of entry or brand introduction on channel competition and channel power changes. A key challenge in our application was to isolate the competitive conduct effects from demand and cost changes. We build a model of wholesale and retail pricing for the toothpaste market by specifying each player’s objective function as a combination of profits and shares. This formulation enables us to parsimoniously isolate the changes in competitive conduct.

Our results show that changes in the retail price are attributable to changes in manufacturer and retailer competitive conduct, and demand; cost changes are relatively small. We find that incumbents’ response to brand introduction is a function of the entrant’s brand introduction stance. For example, a de novo non-aggressive brand introduction is accommodated
more aggressively than an existing incumbent’s aggressive brand extension. We find that brand introduction upstream did not increase competition upstream enough to transfer more power to the retailer, perhaps because of the dominance of two large brands upstream. Also, contrary to what one might expect, an entrant with the right entry competitive strategy is not necessarily disadvantaged relative to incumbent brands.

There are several directions in which this research can be enhanced. While our enhanced pricing objective captures supergame-theoretic consistent equilibria in the tradition of strategic incentive design, more explicit dynamic models of channels conduct would be instructive. Furthermore, our research treats product entry as exogenous. Modeling entry decisions in the presence of channel intermediaries and their anticipated response can add insights, even if adds to complexity of the analysis. We hope our research will spur further developments in this stream of literature.
### Table 1

Descriptive statistics

<table>
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<th>Brand</th>
<th>Share</th>
<th>Promotion (%UPCs on sale)</th>
<th>Retail price</th>
<th>Wholesale price</th>
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</thead>
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<td></td>
<td>Period 1</td>
<td>Period 2</td>
<td>Period 3</td>
<td>Period 1</td>
</tr>
<tr>
<td>A&amp;H-B</td>
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<td>A&amp;H-B + P</td>
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<td>Aqua-B</td>
<td>0.008</td>
<td>0.161</td>
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<tr>
<td>Colg</td>
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<td>0.282</td>
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Table 2
Demand function estimates

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<th>Period 3</th>
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<td>A&amp;H-B + P brand intercept</td>
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<td>Aqua-B brand intercept</td>
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<td>-4.646*</td>
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<td>Colg brand intercept</td>
<td>-1.538**</td>
<td>-1.574</td>
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<td>-5.528**</td>
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<tr>
<td>Price</td>
<td>0.605</td>
<td>0.549</td>
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* = 99% significance
** = 95% significance
Table 3

Own price elasticity

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<td>A&amp;H-B</td>
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<td>Aqua-B</td>
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<td>Ment (S + P)</td>
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* = 99% significance

** = 95% significance
Table 4
Estimates of manufacturer costs and weight on shares

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<td>Weight</td>
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<td>0.095*</td>
<td>-1.300*</td>
<td>0.273</td>
<td>0.095*</td>
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<td>Colg</td>
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<td>0.127</td>
<td>0.003*</td>
<td>-2.042*</td>
<td>0.13</td>
<td>0.015*</td>
<td>-2.064*</td>
<td>0.127</td>
<td>-0.002**</td>
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<tr>
<td>Colg-B</td>
<td>-1.173*</td>
<td>0.31</td>
<td>-0.021**</td>
<td>-1.193*</td>
<td>0.303</td>
<td>-0.072*</td>
<td>-1.173*</td>
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<td>-0.038*</td>
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<td>0.139</td>
<td>-0.003*</td>
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<td>0.022*</td>
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<td>-0.040*</td>
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<td>Crst-B</td>
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<td>0.285</td>
<td>0.079*</td>
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<td>0.292</td>
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<td>0.040*</td>
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<td>-0.035*</td>
<td>-0.680*</td>
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<td>0.058*</td>
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</tr>
</tbody>
</table>

* = 99% significance, ** = 95% significance

Table 5
Breakdown of manufacturer margins

<table>
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<tr>
<th>Brand</th>
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<th>Period 3</th>
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<tr>
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<td>Conduct effect</td>
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<td>Total margin</td>
<td>Conduct effect</td>
<td>Demand effect</td>
<td>Total margin</td>
<td>Conduct effect</td>
<td>Demand effect</td>
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<tr>
<td>A&amp;H-B</td>
<td>0.11</td>
<td>0.004</td>
<td>0.106</td>
<td>0.08</td>
<td>-0.036</td>
<td>0.116</td>
<td>0.085</td>
<td>-0.059</td>
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<tr>
<td>A&amp;H- B + P</td>
<td>0.069</td>
<td>0.001</td>
<td>0.068</td>
<td>0.034</td>
<td>-0.104</td>
<td>0.138</td>
<td>0.044</td>
<td>-0.113</td>
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<td>0.001</td>
<td>0.068</td>
<td>0.034</td>
<td>-0.104</td>
<td>0.138</td>
<td>0.044</td>
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<td>0.157</td>
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<td>0.15</td>
<td>-0.006</td>
<td>-0.156</td>
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<td>Colg</td>
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<td>0.177</td>
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<td>-0.095</td>
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### Table 6
Retailer weights on sales of brands

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<th>Period 3</th>
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<tr>
<td>A&amp;H-B</td>
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<td>-0.041*</td>
<td>0.014*</td>
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<td>-0.017*</td>
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<tr>
<td>Aqua</td>
<td>-0.003*</td>
<td>0.063*</td>
<td>0.025*</td>
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<tr>
<td>Aqua-B</td>
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<td>0.037*</td>
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<tr>
<td>Colg</td>
<td>0.196*</td>
<td>0.214*</td>
<td>0.053*</td>
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<td>0.012*</td>
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<td>Crst</td>
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<td>0.197*</td>
<td>0.021*</td>
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<td>0.088*</td>
<td>0.035*</td>
</tr>
<tr>
<td>Ment- B + P</td>
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<td>-0.142*</td>
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* = 99% significance, ** = 95% significance

### Table 7
Breakdown of retailer margins

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<tbody>
<tr>
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<td>Total margin</td>
<td>Channel Interaction Effect</td>
<td>Demand effect</td>
<td>Total margin</td>
<td>Channel Interaction Effect</td>
<td>Demand effect</td>
<td>Total margin</td>
<td>Channel Interaction Effect</td>
<td>Demand effect</td>
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<td></td>
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<tr>
<td>A&amp;H-B</td>
<td>0.146</td>
<td>0.017</td>
<td>0.129</td>
<td>0.153</td>
<td>0.027</td>
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<td>0.146</td>
<td>-0.022</td>
<td>0.168</td>
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<tr>
<td>A&amp;H- B + P</td>
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<td>0.232</td>
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Table 8
Manufacturer margins (MM) and Retail margin (RM) as percentage of retail price

<table>
<thead>
<tr>
<th>Brand</th>
<th>Period 1</th>
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<th>Period 3</th>
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<td>10.209</td>
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<td>50.000</td>
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References


