One to One Marketing Services:
Optimal Customer and Product Strategy*

Joseph Pancras
University of Connecticut School of Business
Marketing Department
2100 Hillside Road, Unit 1041
Storrs, CT 06269-1041
joseph.pancras@business.uconn.edu
Phone: 860-486-0810
Fax: 860-486-5246

K. Sudhir
Yale School of Management
135 Prospect St, PO Box 208200
New Haven, CT 06520-8200
Email: k.sudhir@yale.edu
Phone: 203-432-3289
Fax: 203-432-3003

June, 2006

* Joseph Pancras is Assistant Professor of Marketing at the University of Connecticut and K. Sudhir is Professor of Marketing at Yale University. The paper is based on an essay from the first author’s dissertation at New York University. The authors thank Joel Steckel, Yuxin Chen, Paris Cleanthous, Russell Winer, Vicki Morwitz and Jiwoong Shin for feedback and helpful discussions and the workshop participants at Carnegie Mellon University, Koc University, London Business School, New York University, Purdue, SUNY Buffalo, University of Central Florida, UC Berkeley, UCLA, University of Connecticut, University of Georgia, University of Southern California, University of Texas at Austin, Washington University at St. Louis and Yale University for their comments.
One to One Marketing Services: Optimal Customer and Product Strategy

Abstract

One to one (1:1) marketing services (e.g., customized advertisements, promotions and direct mail) are a growth industry. Extant research in this area tends to have an engineering emphasis; they focus on developing techniques to use individual-level data to optimize 1:1 services. In contrast, this paper focuses on marketing strategy issues faced by a 1:1 service firm given the availability of the 1:1 technology. Specifically, we develop an empirical framework to evaluate the optimal customer (exclusive/non-exclusive) and product (quality or accuracy of 1:1 customization) strategy for a 1:1 service firm. We illustrate the framework for a 1:1 coupon service firm catering to grocery manufacturers using household purchase history data for the ketchup market. We find that selling on a non-exclusive basis using the maximum available purchase history data is the most profitable strategy in the ketchup category for the 1:1 service firm. We also evaluate the potential impact of the retailer entering the 1:1 coupon service business. Since 1:1 marketing can increase retailer’s profits from goods sold, it is optimal for the retailer to undercut the prices of a pure play 1:1 services vendor.

Keywords: One to One Marketing, Database Marketing, Customer Relationship Marketing, CRM, Coupons, Price Discrimination, Competition, Marketing Channels.
One to One Marketing Services: 
Optimal Customer and Product Strategy

One to One marketing has been on the rise over the last two decades (Peppers and Rogers 1997). A number of firms now specialize in offering one to one services (e.g., individualized advertising, promotion and direct mail services) to consumer marketers to help them improve the efficiency of their advertising and promotion dollars. Table 1 lists some of the major players in the one to one marketing services business. For each of these players, we provide a brief description of their business and report their revenues, market capitalization and growth rates. As can be seen from Table 1, the industry is gaining in importance as reflected in its market valuations as well as revenues and growth rates. Several companies in this industry have revenues in the hundreds of millions of dollars and valuations over a billion dollars.

**** Insert Table 1 here****

The use of scanners in offline retailing and the intrinsic digital nature of online retailing have enabled the easy collection of purchase and other transaction histories. The falling costs of digital storage and computation have made the recording and analysis of vast amounts of purchase history data for 1:1 marketing feasible. In the grocery and drugstore markets, Catalina Marketing obtains purchase history data through cooperating retailers and provides targeted coupons on behalf of grocery manufacturers to households purchasing at that particular retailer.1 On the Internet, companies such as DoubleClick and Tacoda Systems collect past visit data from cooperating websites and use these to deliver targeted advertising for its advertising clients. In the catalog and specialty retailing industry, firms such as Abacus B2C Alliance and i-Behavior™ pool transactional data from over a thousand catalog titles/retailers to offer improved targeted direct marketing services to its members.2

---

1 Catalina Marketing has penetrated about 21,000 of the roughly 34,000 supermarkets in the United States and records about 250 million transactions per week. The 1:1 couponing considerably increases redemption rates. Catalina’s redemption rates for its 1:1 coupons are about 6-9% in contrast to 1-2% for FSI coupons. Catalina’s focus is primarily on grocery and pharmaceutical manufacturers. Revenues from retailer couponing are less than 9% (Catalina’s 2003 10 K).

2 While Abacus collects data only at the catalog level, i-Behavior™ collect data at the SKU level. The Abacus B2C Alliance has 1550 catalogs/retailers who have pooled together data on over 4.4 billion transactions from over 90 million households (Miller 2003). I-Behavior has data on over 1000 mid-sized catalog companies on over 103 million consumers from 89 million households.
Advances in data collection and storage technologies will continue to fuel the growth and scale of 1:1 services firms. Further, advances in promotion delivery technologies to individuals (in-store at the point of purchase; at home through direct mail; online through email; and even by wireless through cell-phones when on the move) increases the effectiveness and timeliness of 1:1 marketing strategies. Not surprisingly, 1:1 advertising and promotions are pervasive in a wide range of industries including services such as banking, telephony, insurance, durable goods such as autos, and the vast range of products sold in supermarkets and drugs stores. Despite their growing economic importance, there is little empirical research addressing strategic issues of concern to this industry.

Extant research on this industry to-date tends to be of an “engineering” nature focusing on how firms should use individual browsing/purchasing data to personalize advertising or promotions. This research has occurred in marketing, information systems and computer science. (e.g., Ansari and Mela 2003, Liu and Shih 2005, Adomavicius, Sankaranarayanan, Sen and Tuzhilin 2005) and is typically positioned as a means by which a firm can take advantage of its internal databases to improve marketing effectiveness. From the 1:1 services industry perspective, this research develops the technology to create their personalization services. In contrast to such “engineering” research, this paper focuses on “marketing” problems facing the 1:1 services firm. Specifically, we ask the question: conditional on the availability of the 1:1 technology, what is the optimal customer and product strategy for a 1:1 services firm?

In practice, there is considerable diversity in the customer and product strategies of 1:1 services firms. Some sell 1:1 services on an exclusive basis, while others sell on a non-exclusive basis. For example, Catalina sells on an exclusive basis to only one grocery manufacturer in a particular category in any given time period. In contrast, Abacus and i-BehaviorTM sell on a non-exclusive basis to any catalog marketer or specialty retailer who requests their services.

The firms also differ in their outlook toward increasing the accuracy of their targeting services. Catalina voluntarily restricts the length of transaction history used for couponing to a maximum of 65 weeks. In contrast to Catalina, a company such as Abacus continues to expand

---

3 Catalina divides a year into four thirteen-week periods and divides the United States into several regions in defining the product. They divide a retailer’s product offerings into hundreds of finely divided categories (currently over 500 categories). Within a region, in a given time period, Catalina offers the 1:1 coupon service on an exclusive basis to manufacturers within a product category.

4 Catalina’s offers two types of targeting services: (1) Checkout Coupon®, based on last purchase data and (2) Checkout Direct® based on 65 weeks of purchase history data.
the accuracy of its database. Abacus pools data from over 1550 catalog marketers/specialty retailers on over 90 million households and continues to increase the extent of household purchase information in its database. Abacus uses data for up to 5 years on each household in its database.\(^5\)

It is possible that the existing strategies of a firm may have arisen due to historical reasons, but may not be optimal in the current environment. For example, Catalina may have chosen an exclusive strategy because it served as a convenient sales pitch initially to prospective clients that they can have a competitive advantage by working with Catalina. But with its current widespread acceptance by grocery manufacturers, exclusivity may no longer be necessary to win clients. In contrast, since Abacus uses a cooperative approach to collect data from its members, it may not be possible for Abacus to discriminate among its members by using a non-exclusive strategy. Similarly, Catalina’s choice of restricting transaction histories to 65 weeks may have been due to the relatively high cost of storage two decades ago. Firms such as Abacus and i-Behavior\(^*\) may have been able to use longer histories because of their comparatively recent entry into these markets, by which time data storage costs had reduced considerably.

Can 1:1 marketing service firms benefit from changing their current customer and product strategies? Currently, there is little research to guide 1:1 service firms on what the optimal strategy should be. In this paper, we offer an empirical framework to help a 1:1 services firm arrive at an optimal customer and product strategy. We illustrate the framework for a 1:1 coupon service firm such as Catalina using data from the ketchup market. Therefore the details of the empirical modeling in this paper will be tailored to the environment in which Catalina operates. However, the approach can be applied in other empirical contexts with appropriate modifications for the specific characteristics of that context. For example, the framework can be used to help answer whether DoubleClick should sell its targeted advertising services on an exclusive basis or a non-exclusive basis. For this, we need to calibrate the impact of advertising (as opposed to couponing) on the downstream firms’ profitability, but the rest of the analysis would be similar.

---

\(^5\) When DoubleClick purchased Abacus in 1999, it sought to further improve accuracy by combining the offline data from Abacus with online transaction behavior captured by DoubleClick. DoubleClick however did not combine their offline and online data because privacy advocates vehemently opposed the idea and it created a public relations problem for Catalina.
The timeliness of this research question is highlighted in a recent stock analysis report about Catalina by Deutsche Bank (Ginocchio, Chesler and Clark 2005) on how this $1.4 billion market capitalization company can grow further, given that it has achieved virtually complete penetration at all major supermarkets within the U.S. The report states: “Categories are sold on four thirteen-week cycles with exclusivity (only one manufacturer can promote that category during that period). As Catalina believes that only approximately 20-25% of its customers want exclusivity, they are looking at ways to potentially sell more than one manufacturer in a category.” Our approach will provide Catalina an empirical basis to answer this critical business question that it currently faces.

In the grocery context, the retailer is the source of the purchase history data used for 1:1 coupon services. Catalina’s business model is predicated on cooperation from the retailer. A natural question that arises is: What if the retailer becomes the 1:1 services vendor, bypassing Catalina? Large retailers with the appropriate infrastructure could easily implement such a targeting solution. In fact, Tesco in the U.K. has been successfully collaborating with dunnhumby, a U.K. based firm in the development of 1:1 marketing services that includes targeted couponing over the last decade (Humby 2004, Humby, Hunt and Phillips 2003). In the U.S., dunnhumbyUSA is a joint venture between Kroger and dunnhumby that seeks to replicate dunnhumby’s success in the U.K. with Tesco. We find that by providing targeting services, the retailer can also increase profits from the goods sold; therefore the retailer has an incentive to undercut Catalina’s price for the 1:1 service.

We also evaluate the profits for Catalina by providing targeting services to retailers. We find that the profit from providing the 1:1 targeting service to the retailer is greater than that from providing the service to the manufacturers. This suggests that retailer services are potentially an underutilized revenue stream for Catalina. But a practical problem in aggressively pricing retailer services is that retailers may balk at having to provide the data and then paying for services using the same data. Catalina may therefore have only limited bargaining power to extract retailer’s value from targeting, compared to its power over manufacturers. This might explain why Catalina aggressively markets its manufacturer service compared to its retail services. Currently, retail services provide less than 9% of Catalina’s total revenues, while manufacturer services provide more than 53% of revenues.
Tradeoffs in Choosing the Optimal Customer and Product Strategy

What are the tradeoffs facing the 1:1 service provider in deciding the optimal customer and product strategy? To fix ideas and to facilitate empirical work, we illustrate the tradeoffs in the context of Catalina for the ketchup category where there are two main competitors: Heinz and Hunt’s. Unlike standard products or services, where the economic value to a customer is independent of who else uses it, the value of Catalina’s 1:1 coupon service for Heinz depends on whether Heinz uses the service exclusively or whether Hunt’s also uses it. This is because the effectiveness of a 1:1 coupon for Heinz in increasing sales is a function of whether Hunt’s also offers targeted coupons.

What is particularly interesting is that the economic value of the service for Heinz may be higher or lower if Hunt’s also uses the service; i.e., this service can have positive or negative externalities. If the service has positive externalities, it makes obvious sense for the firm to sell its service to both Heinz and Hunt’s. If it has negative externalities, then Catalina would have to evaluate whether the negative externalities for Heinz and Hunt’s are sufficiently low to still sell to both; if not, it would have to sell the service on an exclusive basis to only one of them depending on who has the higher willingness to pay (higher economic value). Thus the optimal customer strategy of whether to sell on an “exclusive” basis to Heinz or on a “non-exclusive” basis to multiple manufacturers is an empirical question for Catalina.

Thus far in this scenario, we have treated the “product,” i.e., the quality of the targeting that Catalina offers as fixed. In the context of 1:1 marketing, the quality of the targeting is related to the accuracy with which a firm (e.g., Heinz) can identify the segment it seeks to target. Catalina can increase the accuracy of targeting in a number of ways: (1) use demographic information; (2) increase the length of purchase history of households within a category at a cooperating retailer; (3) use information about purchasing behavior in other categories at the cooperating retailer to take advantage of cross-category similarities in purchase behavior (e.g., Ainslie and Rossi 1998); and (4) combine information about purchasing behavior of households from other retailers. In this paper, we only consider the first two options to improve targeting accuracy.6

---

6 Optimal targeting using cross-category purchase behavior is computationally very cumbersome; hence beyond the scope of our analysis. Catalina does not have the option to pool information across retailers, because it is contractually obliged not to pool information across retailers. Households are identified only by a retailer’s internal
What is the optimal product strategy for Catalina? For most products/services, firms would like to maximize the quality of their products/services if increasing quality were relatively costless. However, 1:1 targeting is different in that increasing the quality of targeting may reduce the economic value of the service for the downstream clients. The idea is simple: if the targeting service is sold on an exclusive basis to only Heinz, the economic value of the targeting service for Heinz will definitely increase because Heinz can more effectively price discriminate its customers. But if the targeting service is sold to both Heinz and Hunt’s, the price discrimination effect of targeting can be overwhelmed by the more intense competition created by targeting (e.g., Shaffer and Zhang 1995). Whether the price discrimination effect or competition effect dominates is moderated by the level of targeting accuracy (Chen, Narasimhan and Zhang 2001). At low levels of accuracy, price discrimination effects dominate competition effects. But at high levels of accuracy competition effects dominates price discrimination effects. Thus Catalina could potentially destroy economic value to downstream clients by increasing accuracy if it sold the product on a non-exclusive basis to both firms (Heinz and Hunt’s). Then, Catalina may find it optimal to increase accuracy, but sell on an exclusive basis to only one of the firms to reduce the competition effect. Alternatively, it could reduce accuracy and sell to both firms and thus extract greater total revenues from both. Therefore the customer strategy and the product strategy of a 1:1 service firm are intertwined and the empirical question of what is the optimal strategy for a particular 1:1 services firm needs to be determined in the relevant empirical context.

Further, it is important to note that theoretical models abstract away from many complexities of real world markets, but these need to be accounted for in an empirical model. For example, theoretical models have typically allowed for household heterogeneity only on horizontal attributes, but in reality households are also heterogeneous on vertical attributes. On the supply side, the theoretical models abstract away from the fact that manufacturers do not sell directly to the consumer, but through a retailer. The empirical analysis needs to model the real world demand and supply characteristics appropriate for the particular market in order to arrive at the correct product and customer strategies for the 1:1 services firm.

identification number (say from a loyalty program) and therefore Catalina cannot pool information across multiple retailers.
Literature Review

This paper is related to both theoretical and empirical research streams on 1:1 pricing. The literature refers to 1:1 pricing broadly using terms such as targeted couponing and behavior based pricing. Using similar models, This and Vives (1988) and Shaffer and Zhang (1995) showed that in a competitive market, spatial discriminatory pricing or targeted coupons lead to a prisoner’s dilemma relative to uniform pricing. These models assumed symmetric firms. Shaffer and Zhang (2002) show that in the presence of firm asymmetry, higher quality firms with larger market shares can improve volumes and profits due to gains in market share though they continue to get lower profit margins due to increased competition. Importantly, as discussed earlier, Chen, Narasimhan and Zhang (2001) showed that the level of targeting accuracy moderates the profits from 1:1 promotions. They show that there is an inverted-U shaped relationship between profitability and accuracy of targeting (personalization).

There is also a growing literature on behavior based pricing (e.g., Chen 1997, Villas-Boas 1999; Fudenberg and Tirole 2000; Shaffer and Zhang 2002; Chen and Zhang 2004). These papers generally find that behavior based pricing leads to a prisoner’s dilemma. Taylor (2003) and Villas-Boas (2004) highlight the effects of “strategic” consumers who alter purchasing behavior to avoid revealing their preferences.

The paper is also related to the theoretical literature on information suppliers and investments in information. Iyer and Soberman (2000) model how the downstream competition between firms who use product modification information affects the marketing strategies of the information supplier. In a similar spirit, our paper empirically analyzes how the marketing strategies of the 1:1 coupon services firm are affected by how grocery manufacturers use the service downstream. Chen and Iyer (2002) study how firms may differentially invest in addressability to avoid the negative effects of downstream competition.

In terms of empirical research on 1:1 pricing, Rossi, McCulloch and Allenby (1996) and Besanko, Dube and Gupta (2003) evaluate the profitability of targeted coupons. Rossi, McCulloch and Allenby (1996) investigate how manufacturers can improve their profits with increasing levels of purchase history and demographic information. Unlike this paper, they do not model the retailer or competition between manufacturers. Besanko, Dube and Gupta (2003) only study the profitability of targeting using only last visit data, but model both competition and the retailer. However, unlike this paper, neither paper investigates the 1:1 service provider’s
strategic decisions. Our analysis also finds that these two papers over-estimate the profitability impact of personalization. This is because the models of consumer behavior used in computing profits with and without targeting are different. We discuss this issue in detail when reporting our result on incremental profits. In terms of 1:1 advertising/communication, Ansari and Mela 2003 develop algorithms for how a firm should use consumer history to customize email communications.

Model

Figure 1 represents a schematic of the grocery markets in which Catalina operates. There are four sets of agents involved in this market: (1) The 1:1 service provider (e.g., Catalina) (2) the manufacturers (3) a retailer and (4) consumers.

The model of manufacturers selling through a retailer to the consumer has been studied in previous research (e.g., Sudhir 2001, Berto Villas-Boas 2004, Villas-Boas and Zhao 2005). In these models, the pricing decisions of manufacturers and retailers are modeled as endogenous. The model in this paper expands on this literature by endogenously modeling the decisions faced by a 1:1 coupon service provider who facilitates targeted couponing to consumers in the market. Since Catalina is contractually obliged not to pool purchase history data across multiple retailers, the assumption that Catalina uses only data from one retailer for its targeting service is consistent with institutional reality. As in most previous research (e.g., Besanko, Gupta and Jain 1998; Besanko, Dube and Gupta 2003; Sudhir 2001), we assume that the retailer is a local monopolist. Berto Villas-Boas (2004) indeed finds very little evidence for cross-retailer competition at the single category level.

Figure 2 represents the schematic of the decision alternatives faced by a 1:1 coupon service provider such as Catalina (1:1 SP) regarding the sales of its services. We model the timing of the game into two phases: Phase 1 which involves the sale of 1:1 services and Phase 2 which involves the sale of consumer goods. Below we describe the different stages of the Phase 1 decision related to the sale of targeting services.

*** Insert Figure 2***

**Phase 1: Sale of 1:1 Services**

**Stage 1: Catalina’s Product Choice Decision:** At this stage, Catalina decides on the length of purchase history it should optimally use for targeting. Here we consider three alternatives: (1)
Last Visit, along the lines of targeting used in Besanko, Dube and Gupta 2003, (2) Last Purchase, as used by Catalina in its Catalina Coupon® program and (3) Full Purchase History, along the lines of what Catalina uses in its Catalina Direct® program.7

Stage 2: Catalina’s Initial Customer Choice and Price Decision: For ease of exposition, we will consider a market with two national brand manufacturers. Catalina has three alternatives to make initial offers at this stage: (1) Offer the 1:1 service to Firm 1 and set its price ($p_1^f$); (2) Offer the 1:1 service to Firm 2 and set the price ($p_2^f$); and (3) Offer the 1:1 service to both firms and set the prices to both firms ($p_1^b, p_2^b$).

The subscripts “1” and “2” on prices refer to the price charged to firms 1 and 2. The superscript ‘$f$’ refers to the fact that firm 1 or 2 is ‘first’ offered the service exclusively. The superscript ‘$b$’ refers to the situation when both firms are initially offered the service on a non-exclusive basis.

Stage 3: Initial Offer Acceptance/Rejection by Manufacturers: Manufacturers decide whether to accept or reject the offer of 1:1 services at the offered prices. In the case where one firm is exclusively offered and accepts the offer, the manufacturers and retailers then move to the second “sales of goods” phase with one of the firms having the capability to target. If both firms were offered initially, then there are four possible outcomes: where one of the firms accepts, both accept and neither accept. Given these outcomes, the manufacturers and retailers then move to the sales of goods phase with the firms that have accepted the 1:1 service offers having the capability to target.

Stage 4: Catalina offers 1:1 Service to “Other” Manufacturer at Second Offer Price: If one firm is exclusively offered the 1:1 service first and rejects it, then Catalina will offer the service second to the other firm on an exclusive basis. For example, if Firm 2 receives the offer after Firm 1 rejects the initial offer of exclusive service, this price to firm 2 will be denoted as ($p_2^s$), where the superscript ‘$s$’ indicates the firm 2 was offered the service second after firm 1 refused.

Stage 5: Second Offer Acceptance/Rejection by Manufacturers: Manufacturers who received the second offer can either accept or reject the offer for the 1:1 service.

Given these decisions, the manufacturers and retailers then move to the second phase (sales of goods) with the firms that have accepted the 1:1 service offers having the capability to target.

7 Catalina restricts the full purchase history to only 65 weeks, but we evaluate different lengths of purchase history.
The payoffs realized after the second phase are shown in three rows in Figure 2. We denote the profits from the sale of goods to manufacturer ‘f’ by $\Pi_f^{xy}$, where $x$ and $y$ refers to the 1:1 service purchase decisions of firms 1 and 2 respectively. A value of 1 (0) refers to whether the firm uses (does not use) the 1:1 services. The first row indicates the payoff to the 1:1 service provider (i.e., price charged for 1:1 services), the second and third rows indicate the payoffs to Firms 1 and 2 respectively which shows the net profits from the sale of goods and the fees paid (if any) to the 1:1 service provider.

It is important to note that in this game of complete information, Stages 4 and 5 are in the off-equilibrium path, because Catalina will offer the right price in the initial offer so that whoever is offered initially will accept. We have marked the equilibrium paths in bold. Hence, even though there are 10 payoff matrices shown, the only relevant payoffs in equilibrium are the three payoff matrices where the firms that are initially offered the 1:1 service by Catalina accept the product. Nevertheless, the payoffs from the off-equilibrium paths are critically important for Catalina to figure out what price it should charge the firms in Stage 2. This is because Catalina’s offer price to the firms should take into account the incremental profits a firm will make relative to the outcome where the competitor obtains exclusive use of 1:1 services. It should be noted that the price charged is not with respect to the situation where there is no targeting at all. This is because the scenario where neither firm purchases 1:1 coupons will not be on the sub-game perfect equilibrium path and therefore is not a credible alternative threat to either firm 1 or firm 2. This limits the amount of value that can be extracted from either firm by the 1:1 service provider. Hence $P_1^f = \Pi_1^{00} - \Pi_1^{01}$; $P_2^f = \Pi_2^{00} - \Pi_2^{01}$ and $P_1^b = \Pi_1^{10} - \Pi_1^{01}$; $P_2^b = \Pi_2^{10} - \Pi_2^{01}$.

**Phase 2: Sales of Goods**

**Stage 1**: Manufacturers set wholesale prices and the coupon face values for individual households. If they have not purchased the 1:1 services, all households are assumed to have a coupon face value of zero.\(^8\)

**Stage 2**: Retailer takes the information about wholesale prices and coupons issued in setting retail prices. Since the coupons are issued by the retailer, it is reasonable to assume that the

---

\(^8\) Technically, manufacturers set the wholesale prices and Catalina decides whether to offer the coupon and what is face value will be, but this distinction is unimportant for the results after the manufacturer has made the decision to purchase the targeting service.
retailers take into account the coupons issued in setting retail prices.\(^9\) We follow previous research (Rossi, McCulloch and Allenby 1996, Besanko, Dube and Gupta 2003) in assuming that coupons are valid only for the week of issue.

**Stage 3:** Given the retail prices and coupons issued, the household makes buying decisions in order to maximize utility. We now develop a detailed model of these three stages of Phase II.

We describe the decisions faced by each of the players below. We begin with the consumer model, then describe the retailer and manufacturer models respectively.

**Consumer**

A household \(i (i = 1, 2, \ldots, H)\) chooses one of \(J\) available brands (denoted by \(j = 1 \ldots J\)) in the category or decides not to purchase in the category (\(j = 0\), the no-purchase alternative or ‘outside good’) on each household shopping occasion \(t = 1, 2, \ldots, n_t\). Let the vector \(X_{ijt}\) denote all variables for brand \(j\) experienced by household \(i\) at shopping occasion \(t\). This vector includes brand-specific indicators, marketing mix variables such as features, displays, and household-specific variables which depend on the previous purchase/s such as state dependence and household stock on occasion \(t\).

Consumers choose the brand that offers the maximum utility. We specify the indirect utility of household \(i\) for brand \(j (j = 1 \ldots J)\) on shopping occasion \(t\) as follows:

\[
 u_{ijt} = X_{ijt} \beta - r_{jt} \alpha + I_{it} \gamma + \xi_{jt} + \varepsilon_{ijt} 
\]

where \(X_{ijt}\) includes all variables that affect household \(i\)’s evaluation of brand \(j\) on occasion \(t\) (feature, display and lagged brand choice) as well as time invariant brand intercepts, \(r_{jt}\) is the price of brand \(j\) at \(t\), \(I_{it}\) is the inventory stock of household \(i\) in the category (across all brands) at time \(t\), \(\xi_{jt}\) is the brand \(j\)-specific effect on utility at shopping occasion \(t\) that affects all households but which is unobserved by the econometrician, and \(\varepsilon_{ijt}\) is the unobserved utility of brands that vary over shopping occasions across households.

---

\(^9\) For brevity, we only describe the Manufacturer Stackelberg model in the paper, though we also estimate the Vertical Nash model.

\(^{10}\) We calculated inventory as the stock of the relevant category (ketchup) that has accumulated with the household due to previous purchases, with the stock being depleted at the average consumption rate of the household for ketchup. The method of calculating inventory is similar to Gupta (1988). In our model the utility of choosing the outside good, instead of being set to 0 as in Chintagunta (2002) is parameterized by the ketchup inventory stock. In the profit simulations, the probability of purchase in future periods will be affected by the simulated purchase since the inventory variable will be updated and will affect the probability of the outside good choice in future periods.
Since the indirect utility for any item in the choice set is identified only in terms of differences with respect to a base choice in the logit model, we treat the outside good as the base choice and normalize its utility as follows:

\[ u_{i0t} = \varepsilon_{i0t} \]

The elements of the vector \( \varepsilon_{it} = (\varepsilon_{i0t}, \varepsilon_{i1t}, \ldots, \varepsilon_{ik_t}) \) each are assumed to follow an independent Gumbel distribution with mean zero and scale parameter 1.

We model heterogeneity using a latent class framework (Kamakura and Russell 1989). Consumers are probabilistically allocated to one of \( K \) segments, where each segment \( k \) has its own parameter vector \( (\alpha^k, \beta^k) \). The size of segment \( k \) is denoted as \( f^k \), which can be interpreted as the likelihood of finding a consumer in segment \( k \), or the relative size of the segment in the population of consumers. The probability of household \( i \) that belongs to segment \( k \) choosing a brand \( j \) is given by:

\[
S_{ijt}^k = \frac{\exp(X_{ijt}^{\beta^k} - r_{ijt}^{\alpha^k} + I_{ijt}^{\gamma^k} + \xi_{jt})}{\sum_l \exp(X_{ijt}^{\beta^k} - r_{ijt}^{\alpha^k} + I_{ijt}^{\gamma^k} + \xi_{lt})} \tag{2}
\]

Note that \( \xi_{jt} \) are the common demand shocks that affect all consumers. These are observable by the price-setting firms and consumers in the market but unobservable by the researchers. Villas-Boas and Winer 1999 show that profit-maximizing firms will take \( \xi_{jt} \) into account when setting prices, therefore price is correlated with \( \xi_{jt} \). This causes a price endogeneity problem. Without correcting for endogeneity, the price coefficient will be biased towards zero. We will discuss how we address this issue in the estimation section.

Because \( f^k \) represents the likelihood of finding a consumer in segment \( k \), the unconditional probability of choice for brand \( j \) by consumer \( i \) in time period \( t \) can be computed as:

\[
S_{ij} = \sum_{k=1}^{K} f^k S_{ij}^k = \sum_{k=1}^{K} f^k \left( \frac{\exp(X_{ijt}^{\beta^k} - r_{ijt}^{\alpha^k} + I_{ijt}^{\gamma^k} + \xi_{jt})}{\sum_l \exp(X_{ijt}^{\beta^k} - r_{ijt}^{\alpha^k} + I_{ijt}^{\gamma^k} + \xi_{lt})} \right) \tag{3}
\]

---

11 The latent class model with discrete segments has considerable empirical validity and managerial relevance (Wedel and Kamakura 2000). A competing model is one which characterizes consumer heterogeneity using a continuous heterogeneity distribution (Gonul and Srinivasan, 1993). Andrews, Ainslie and Currim (2002) find that both the discrete and continuous heterogeneity distributions fit the data fairly well, though some papers have argued that continuous heterogeneity coupled with discrete heterogeneity can fit the data better (Allenby, Arora and Ginter 1998). In this paper, we apply the latent class approach because of its computational tractability when solving for the equilibrium targeting prices when competitive and retailer reactions are incorporated in the model.
Once the estimates of the latent class model are obtained, one can apply the Bayes’ rule on the aggregate latent class estimates using each household’s purchase history that is available. The posterior probability that a consumer ‘i’ belongs to a segment ‘k’ conditional on observed choice history $H^i$ is obtained by revising the prior probability of membership $f^k$ in a Bayesian fashion (Kamakura and Russell 1989):

$$Pr( i \in k | H^i ) = \frac{L(H^i | k) f^k}{\sum_k L(H^i | k') f^{k'}}$$

(4)

Using different levels of household choice history will result in different levels of posterior probability for each consumer $i$. The posterior probability using the entire purchase history for the consumer $i$, which we will denote by $H^i_{FH}$, plays an important role in our analysis, and we denote the corresponding posterior probability as:

$$Pr( i \in k | H^i_{FH} ) = \frac{L(H^i_{FH} | k) f^k}{\sum_k L(H^i_{FH} | k') f^{k'}}$$

(4a)

Retailer

The retailer’s goal is to maximize category profits in time period $t$, given the decisions to buy 1:1 services by manufacturers. Let $x = 1(0)$ denote whether manufacturer 1 has purchased (not purchased) the personalization service. Similarly, let $y = 1(0)$ denote whether manufacturer 2 has purchased (not purchased) the personalization service. Therefore the retailer chooses retail prices $r_{1t}^{xy}, \ldots, r_{2t}^{xy}$, conditional on which firms have purchased the 1:1 service to solve the following problem:

$$\max r_{1t}^{xy}, \ldots, r_{2t}^{xy} \prod_{j=1}^{J} \sum_{i=1}^{N_j} [r_{jt}^{xy} - w_{jt}^{xy}] S_{jt}([r_{jt}^{xy} - D_{jt}^{xy}], M_t)$$

(5)$^{12}$

where $D_{jt}^{xy}$ is a matrix of individual specific coupon values as described earlier under the alternative scenarios where the different manufacturers purchase the targeting service, and $M_t$ is

$^{12}$ In the following equations, we use the square brackets for grouping terms and the parentheses for denoting arguments of function. For example, in equation 5 the right hand side consists of (1) the retail margin $[r_{jt}^{xy} - w_{jt}^{xy}]$, (2) the share $S_{jt}([r_{jt}^{xy} - D_{jt}^{xy}])$, which is a function of the effective price faced by the consumer of $r_{jt}^{xy} - D_{jt}^{xy}$ and (3) $M_t$, the total market size in time $t.$
the total size of the market on occasion \( t \). The shares \( S_{ijt} (r_{ijt}^{xy} - D_{ijt}^{xy}) \) in the above equation are the weighted average of the segment-specific shares across the \( k \) segments at the effective price faced by the consumer of \( r_{ijt}^{xy} - D_{ijt}^{xy} \). Taking the first order conditions of equation (5) with respect to retail prices, we obtain the retailer’s pricing equation for each product in the category in terms of wholesale prices. The details of the derivation are provided in Appendix A. The retailer price equation is shown in equation A5 of the appendix.

**Manufacturer**

A manufacturer ‘\( m \)’ offering a subset \( N_m \) of brands in the market sets the wholesale price \( w_{jt}^{xy} \) (where \( j \in N_m \)) and the coupon face values to individual households \( (D_{ijt}^{xy}) \) so as to maximize the manufacturer’s profits. A manufacturer who has not been sold the personalization service will have coupon face values set to zero. The manufacturer takes into account the knowledge that retailer prices \( (r_{ijt}^{xy}) \) will be set taking into account the wholesale prices and the coupon face values that have been issued to individual households. The profit of manufacturer \( m \) at time \( t \) from the sales of goods is given by:

\[
\Pi_{mt}^{xy} = \sum_{j \in N_m} \sum_{i=1}^{N} \left[ w_{jt}^{xy} - D_{ijt}^{xy} - c_{jt} \right] S_{ijt} \left( (r_{jt}^{xy} (w_{jt}^{xy}, D_{jt}^{xy}) - D_{ijt}^{xy}) \right) M_t 
\]

(6)

where \( c_{jt} \) is the marginal cost of the manufacturer for brand \( j \) in period \( t \), and \( S_{ijt} (r_{jt}^{xy} (w_{jt}^{xy}, D_{jt}^{xy}) - D_{ijt}^{xy}) \) is the probability of household \( i \), buying brand \( j \) in period \( t \) given the decisions of manufacturers 1 (denoted by \( x \)) and 2 (denoted by \( y \)) to buy the purchase history data. Note that the retailer sets the retail price taking into account both the wholesale price \( (w_{jt}^{xy}) \) and the vector of discounts offered to all households, i.e., \( D_{ijt}^{xy} = \{ D_{ijt}^{xy} \}_{i=1}^{H} \).

We can write the manufacturer profit equations at the individual level as follows:

\[
\Pi_{mt}^{xy} = \sum_{j \in N_m} \left[ w_{jt}^{xy} - D_{ijt}^{xy} - c_{jt} \right] S_{ijt} \left( (r_{jt}^{xy} (w_{jt}^{xy}, D_{jt}^{xy}) - D_{ijt}^{xy}) \right) 
\]

Taking the first order conditions of (6), with respect to \( w_{jt}^{xy} = w_{jt}^{xy} - D_{ijt}^{xy} \), we are able to solve for the effective margin from each household. Then the wholesale price will be \( w_{jt}^{xy} = \max_i w_{jt}^{xy} \) and \( D_{ijt}^{xy} = w_{jt}^{xy} - w_{jt}^{xy} \). The derivation is detailed in the Appendix A.
It is important to note that though the assumed demand models entering the objective functions of the manufacturer and the retailer (and the chosen optimal wholesale prices, household discounts and retail prices) will reflect the level of information that is available to the market participants based on whether they have access the 1:1 marketing service, the actual demand and the resultant profits resulting from such pricing strategies will reflect the “true” behavior of the consumer (which we approximate using estimates from using full purchase history of the consumer $H_{ff}^{i}$). We elaborate on this further when reporting the profits to manufacturers and retailers from using 1:1 targeting.

We specify manufacturer marginal cost as a function of factor prices, which assumes a fixed proportions production technology.

$$c_j = \lambda_j + \theta^* B_j + \nu_j$$  \hspace{1cm} (7)

where $B_j$ are the factor prices, $\lambda_j$ are brand specific intercepts and $\nu_j$ is the cost shock.

**Estimation and Solution Strategy**

The solution strategy consists of the following five steps, where the first two steps involve estimation to characterize the market and the remaining three steps involve policy simulations to infer the optimal strategy for the personalization service firm.

**Step 1**: Estimate the demand and supply model discussed above. The demand model is a latent class model of household preferences and responsiveness to marketing mix with alternative levels of purchase history lengths used to proxy for personalization quality from consumer information.\(^{13}\) To account for potential price endogeneity concerns, we use the control function approach developed by Petrin and Train (2004). The control function approach has similarities to Rivers and Vuong (1988) and Villas Boas and Winer (1999). Essentially, we obtain residuals from a regression of prices of the different brands against its cost factors and include these residuals in the utility equation (1) in estimating the demand model. More details of the control function approach are explained in appendix B. Given the demand estimates, we can compute the wholesale and retail margins using the equations A3 and A9. Then the cost estimation reduces to a linear regression, where the dependent variable is (Retailer price – Computed Retail Margin –

\(^{13}\) Other aspects of consumer information, such as consumer demographics could potentially improve the quality of the personalization service, but the incremental impact of demographics over purchase history was miniscule in our analysis. So we focus on purchase history length as a measure of accuracy and omit demographics in further analysis. This is consistent with the findings in Rossi, McCulloch and Allenby (1996).
Computed Wholesale Margin) and the independent variables are the cost factors and the brand dummies.

**Step 2:** Apply Bayes’ rule on the aggregate latent class estimates using each household’s purchase history (the length of history varies depending on the scenario being considered and the number of visits of the household during the estimation period) to obtain household level probabilities of membership in each of the latent classes. When purchase histories are short, the individual level probabilities differ very little from the aggregate probabilities and as the purchase histories lengthen, the individual probabilities tend to become more different from the aggregate probabilities reflecting more closely the idiosyncratic preferences of the household. The manufacturers may use varying levels of information about consumer purchase history in targeting them.

**Step 3:** Having thus characterized the household level preferences using different lengths of purchase history data, solve for the optimal prices and discounts under alternative targeting scenarios (exclusive, non-exclusive). To obtain steady state profit estimates, solve for prices and discounts over a large number of weeks tracking both consumer past purchases (to account for state dependence effects) and inventories (to account for inventory effects on category purchases) over this period. In solving for the equilibrium prices and discounts, take into account not only the pricing behavior of the manufacturers, but also the equilibrium passthrough behavior of retailers. The same marketing mix variables for features and displays as in the estimation data are used in this simulation.

**Step 4:** Given the optimal prices and discounts computed based on Step 3, evaluate manufacturer profits based on consumer choices, at the optimal prices and discounts. Note that optimal prices and discounts will vary depending on the available purchase history and which firms do targeting. However consumer behavior should be based on the same “true” preferences irrespective of what data firms have. Hence in predicting consumer choice, given the chosen prices and discounts, it is critical to always use the household level estimates obtained using the full purchase history data, because these are our best estimates of the “true” household behavior. One should not use the estimates obtained with shorter purchase histories at this stage as this will grossly overstate the profitability of targeting. On first glance, this issue may appear a “mere detail”, but we find that the improvements in profits in earlier empirical papers (Rossi,
McCulloch and Allenby 1996; Besanko, Dube and Gupta 2003) can be overstated if we do not assume a “true” stable consumer behavior based on the full purchase history.

Step 5: Given the profits obtained under alternative targeting scenarios of history length (full purchase history, only last purchase, only last visit, no targeting) and client choice (exclusive, non-exclusive), solve for the optimal customer and product strategy for the 1:1 service provider.

**Empirical Illustration**

*Data*

We use the AC Nielsen scanner panel data on the ketchup category from the largest retailer in the Springfield, MO market for the empirical illustration. We restrict attention to the four largest brand-sizes which collectively account for 64% of the sales in this category: Heinz 32 oz, Hunt’s 32 oz, Heinz 28 oz, and the Store Brand 32 oz and use 100 weeks of purchase history data during 1986 to 1988. We use a sample of 143 households based on whether they made at least five purchases of the chosen brand-sizes during the 100 weeks of analysis. The 143 households bought ketchup in 1073 visits out of the total 11660 store visits.

The summary of brand shares (conditional on purchase) and prices are given in Table 2.

*** Insert Table 2***

We use the price of tomatoes as a cost factor. The price data was obtained from the Bureau of Labor Statistics (BLS). Part of the data was obtained from the website and the rest through email from BLS officials.

*Estimation Results*

Based on the Bayesian Information Criterion (BIC), we found that a three segment latent class model is the best model.\(^{14}\) The identification of the latent class logit model with exogenous variables is standard. However, price is endogenous, and as discussed earlier, we use a two step control function approach to obtain unbiased estimates of the price coefficient.\(^{15}\) A first stage regression of ketchup prices with brand intercepts and factor costs (cost of tomatoes) was used.

---

\(^{14}\) Since the AIC and BIC criterion were worse for the model that included demographic and seasonality variables, we report only results of the best fitting model without demographic and seasonality variables. We also considered serial correlation in the effects of marketing variables and the error terms using the geometric decay approach outlined in Seetharaman (2004), but these did not improve model fit.

\(^{15}\) We tested for possible endogeneity of features and displays by using the Hausman test (Hausman 1978) to test for endogeneity, and found that we cannot reject the null hypothesis that feature and display are exogenous even at the 10% level of significance. The test statistic is 14.2 and the critical value at the 5% (10%) significance level of the chi-square distribution with 27 degrees of freedom is 40.1 (36.7).
The key identifying assumption is that the factor costs are independent of the demand shocks. The F-statistic for the tomato cost is 7.8, which is significant at the 5% level. Interacting tomato cost with the brand dummies, as in Villas-Boas and Zhao (2005), caused the F-statistics to become insignificant. Hence we use a common slope coefficient across brands in the first stage regression. We also considered other cost factors such as wages and cost of packaging materials (glass and plastic) as instruments, but did not find these to be effective instruments.

We use the residuals of the first stage regression as an additional variable in the utility equation to estimate the demand model. The demand estimates are presented in Table 3 below. Segment 2 is the least price sensitive, but also purchases least in the category based on the negative coefficients associated with the intercept. It is 24% of the market. Segments 1 and 3 are more price sensitive than segment 2 and together constitute 76% of the market. However Segment 1 is relatively more loyal to Heinz 32 oz. Segment 3’s preferences are more diffused across all brands and is the most price sensitive segment in the market, suggesting the least amount of loyalty. They were also relatively insensitive to inventory levels. This suggests that this segment does not purchase ketchup at regular intervals, but opportunistically buy any brand when it is on sale.

*** Insert Table 3 ***

The price elasticities for the three segment latent class demand model are reported in Table 4. The own and cross price effects are as expected. Hunt’s 32 and the Store Brand 32 have higher own elasticities than the two Heinz brand-sizes. Heinz 28, the most expensive brand, has the lowest own elasticity. Hunt’s 32 and Store 32 have higher cross-elasticities, which indicate that switching would be higher between these brand-sizes. Increase in the price of the largest brand-size Heinz 32, will result in more substantial substitution to Hunt’s 32 and Store 32 rather than Heinz 28.

*** Insert Table 4 ***

Given the estimates of the demand model, we now estimate the supply model. We test for the appropriate manufacturer-retailer interaction (Manufacturer Stackelberg; Vertical Nash) and manufacturer-manufacturer interaction (Bertrand and Collusion). The best fitting model based on a Vuong test (Vuong 1989) is the Manufacturer-Stackelberg model with manufacturers in Bertrand competition (p< 0.01). For this supply model, we report the estimates of the cost factors in the cost equation in Table 5. The estimates suggest that Heinz and the store brand have lower
marginal costs than Hunt’s (though the differences are not significant). Not surprisingly, tomato prices have a significant effect on marginal cost of ketchup.

*** Insert Table 5***

**Analysis of the One to One Services Provider’s Decisions**

Given the demand and cost estimates from the previous section, we now evaluate the profitability of the alternative decision scenarios from the 1:1 service provider’s perspective using simulations. We simulate the market for 100 weeks, which is a sufficiently long period to obtain stable estimates of profits under alternative decision scenarios. From the household level demand model, we get the market share of the sample customers. We then scale this sample market share by the chain’s volume of sales in the week to arrive at chain profits.

We first demonstrate how length of purchase history affects the ability to use 1:1 promotions. We then evaluate the profits of manufacturers (Heinz and Hunt’s) from the sale of goods as a function of whether they use 1:1 coupons either on an exclusive or syndicated basis, i.e., we compute the payoffs \( \Pi_1^{10}, \Pi_1^{01}, \Pi_2^{10}, \Pi_2^{01}, \Pi_1^{11}, \Pi_1^{10} \) for different lengths of purchase history. Using these payoffs, we infer what price the 1:1 marketing service provider can charge under different scenarios and thus arrive at the optimal customer and product decisions of the 1:1 services vendor.

*How Length of Consumer Purchase History affects 1:1 Targeting*

Figures 3a, 3b and 3c show the distribution of posterior probabilities of households belonging to segment 1 when using “last visit,” “last purchase” and “full history” data respectively for targeting. Figure 3a clearly shows that the marketer achieves very little discrimination across consumers by using only information about the last visit, as the vast majority of consumers are classified in the same quintile as the aggregate probability \( f^k \) in Equation 7), i.e., 0.47 for Segment 1. The last purchase information enables more discrimination to be achieved between consumers, as seen in Figure 3b. We achieve much better discrimination among consumers by using 100 weeks of consumer purchase information, as shown in the polarized probabilities in Figure 3c. With 100 weeks of information, almost 40% of consumers

---

16 Average profits per week were very stable with consumer choices simulated over one hundred weeks. Increasing the period of simulation further had no effect on the results, but simply increased computation time.
are assigned with a high degree of probability (posterior probability in the highest quintile) to segment 1, while more than 40% of consumers are not assigned to segment 1 with a high degree of probability (posterior probability in the lowest quintile).

*** Insert Figures 3a, 3b and 3c***

The Effect of 1:1 Coupons on Manufacturer Client Profits

We now assess the profitability of 1:1 targeting for manufacturer clients (Heinz and Hunt’s). An important factor in estimating the profits of manufacturers is the assumption about retailer behavior. We compare results using two assumptions about the retailer (1) the retailer is a category profit maximizer and (2) the retailer charges a simple constant markup over wholesale prices (e.g., Silva-Risso, Bucklin and Morrison 1999); we illustrate with a markup of 25%. The improvement in profits from targeting for Heinz is much greater when the retailer uses a constant markup strategy (9%), compared to when the retailer uses an optimal category profit maximization strategy (2%). However for Hunt’s, the increase in profits from targeting is low (under 1%) under both retailer strategies. In practice, retailers are expected to be somewhere in between the two extremes in their pricing sophistication; we can therefore expect the true benefits of targeting for manufacturers to lie between these bounds.

In the rest of the analysis, we assume that the retailer follows the optimal category profit maximization strategy. The profits under the different scenarios are reported in Table 6. Several insights emerge.

*** Insert Table 6***

First, 1:1 promotions by both firms increase profits relative to no-targeting for all levels of data length (last visit, last purchase and full purchase history). As the reported t-statistics show, these increases are statistically significant. Further, increasing accuracy (from last visit to last purchase and from last purchase to full history) improves profits. The increases are also statistically significant.17 Thus, the positive price discrimination effect of targeting dominates the negative competitive effect of targeting in this market. Even with the full purchase history of 100

---

17 We use bootstrapping to compute the standard errors and t-statistics. We take 30 draws from the distribution of the demand estimates and compute the difference in profits under targeting and no-targeting scenarios for each draw. We perform a paired t-test based on the difference in profits for each draw under the targeting and non-targeting scenarios. Since for most draws, the profits from targeting are better than profits from not targeting, the t-statistics are relatively high even when the profit increases are small. We also find that the profits for both Heinz and Hunt’s using 100 weeks of data are higher (and the difference is statistically significant at p<0.01) than the profits using 65 weeks history (which Catalina currently uses in Checkout Direct®).
weeks and competitive targeting, we have not reached the peak of the inverted U relationship between targeting accuracy and profitability (described in Chen, Narasimhan and Zhang 2001).

Second, we compare the case where only one firm exclusively targets versus the case where both firms target. Under 1:1 targeting using full purchase history, both Heinz and Hunt’s make more profits when both firms target than when either of them targets alone. Thus there is a positive externality from the use of 1:1 targeting for both Heinz and Hunt’s in this market.

Finally, we examine the magnitudes of the improvements in profits from the use of targeting. The maximum profit gain that any firm obtains by using targeted pricing in the ketchup category is about 2%. An improvement of gross margins by 2% can be a substantive increase in net profits. For example, Heinz had a gross margin of 40% and a net margin of 10% in 2003 (Hoover Online). A 2% increase in gross margin can then translate to an increase of about 8% in net margins. As discussed earlier, the 2% increase is a conservative lower bound in the presence of a sophisticated retailer maximizing category profits. The profits can be greater if the retailers are less sophisticated in its pricing.

1:1 Targeting Profits – Measurement Issues

The profits increases from targeting we report are smaller than the profit increases reported in Rossi, McCulloch and Allenby (1996) and Besanko, Dube and Gupta (2003). Using full purchase history data (without demographics), the Rossi, McCulloch and Allenby (1996) study finds an increase of 5% for one item in the tuna category. The Besanko, Dube and Gupta (2003) study finds improvements of 4% for Heinz and 37% for Hunt’s in the ketchup category, merely with the last visit data. We detail below three key modeling issues that can explain these differences.

First, we include inventory in the demand model while the Besanko et al. and Rossi et al models do not. Even though they do not have inventory data, Besanko et al. find suggestive evidence that inclusion of inventories can reduce the potential incremental gain in profits significantly. Category purchase will be overestimated when the effect of inventory is not included in the demand model. Said differently, the absence of inventory in their model implies that consumers who purchase last period are still likely to purchase at the same level in the current period. This overestimates the benefits of accurate price targeting. Rossi et al. use a conditional choice model, so they do not model inventory issues.
Second, the assumption about retailer pricing behavior has an impact on profitability of targeting. Rossi, McCulloch and Allenby (1996) do not consider competitive manufacturer or retailer reaction to targeting. As discussed earlier, the retailer reaction does have an effect on the benefits of targeting: when the retailer charges a constant markup we found that Heinz profits increase by about 9%, a magnitude comparable to the Rossi et al. paper. Therefore this issue needs to be explored further.

Finally, one should maintain a consistent standard of consumer purchase behavior when computing targeting profits. Besanko, Dube and Gupta (2003) compare profits with no targeting using aggregate data and targeting using last visit data. However when computing profits under the two scenarios, they assume different consumer behavior that is consistent with the level of detail of data available for targeting. But since consumer behavior should be invariant to the level of data used to estimate preferences, we use the estimates obtained using full history data as our best approximation of the “true” consumer behavior for targeting with different levels of purchase history.

Table 7 illustrates the magnitude of the bias in the estimates of targeting profits when a consistent standard is not adopted. The first two rows illustrate that using just the information about consumers in characterizing consumer response can result in an ‘increase’ in profit estimates by 10.02% for Heinz and 0.56% for Hunt’s. These two rows are for situations where neither firm targets. The difference is purely a bias introduced due to posterior allocations based on consumer history leading to different shares being estimated for the brands. We note that the ‘profit increases from targeting’ in Table 7 are much higher than the figures we reported in Table 6 and similar to the profit increases reported by Rossi, McCulloch and Allenby (1996) and some of the estimates of Besanko, Dube and Gupta (2003). Future research on targeting needs to take cognizance of this potential oversight when computing profits from targeting.

*** Insert Table 7 ***

Profile of Consumers Targeted

Figures 4a and 4b show the posterior segment probabilities of households targeted by Heinz 32 oz and Hunt’s 32 oz respectively.18 In equilibrium, since Heinz targets almost entirely through coupons for the popular Heinz 32 oz, we profile only households receiving coupons for

---

18 For the sake of exposition in Figures 4a and 4b we label the segments based on some striking characteristics of each segment. Segment 1 is labeled ‘price sensitive Heinz 32 loyals’, segment 2 is labeled ‘light user, Heinz 28 loyals’ and segment 3 is labeled ‘price sensitive heavy users’.
Heinz 32 oz. Heinz 32 oz targets the price sensitive households. Segment 3 (price sensitive, heavy users) receives the most coupons from Heinz; households receiving a Heinz 32 coupon have a 67% probability of being in Segment 3 and 32% probability of being in Segment 1. Heinz thus increase the profit margins from Segment 1 likely households (47% of market size), but competes aggressively with lower prices for Segment 3 likely households (29% of market size). Overall, Heinz offers targeted coupons to about 32% of households in the market.

*** Insert Figures 4a and 4b***

Consumers targeted by Hunt’s 32 are predominantly from segment 3 (the most price sensitive segment, that marginally favors the cheaper Hunt’s brand). Given the lack of strong loyalty, Hunt’s uses coupons to defend market shares in this segment. Hunt’s 32 oz offers coupons relatively infrequently to households belonging to other two segments. Overall, Hunt’s offers targeted coupons to only about 9% of households in the market.

**Identifying Sources of Targeting Profits**

The increase in profits from 1:1 targeting arises from three sources: higher margins, higher brand shares and consumption expansion. Ketchup consumption is unlikely to expand much merely due to couponing; indeed category purchase expansion due to targeting is only 0.2%. We report the effect of targeting on each brand’s shares and profit margins (in the full purchase history case) in Table 8 below. The average margins across all households are calculated by appropriately weighting the margins using household level brand shares.

*** Insert Table 8***

The gain in profits for Heinz 32 oz is essentially from price discrimination. Its average margins increase by about 2.8%, while brand share increased by about 0.3%. In contrast, Hunt’s share goes up by 2.9%, margins increase by 0.7%. As the smaller brand, Hunt’s takes advantage of the increase in prices by Heinz to increase its share (on its smaller base), even with a price increase. Thus Heinz prices less aggressively than Hunt’s, because as the larger brand it is able to gain more from 1:1 pricing.

Targeting by Heinz 32 is more extensive, with about 32% of consumers being targeted compared to only 9% of consumers targeted by Hunt’s 32. The depth of discounts issued by
Heinz is also greater than that of Hunt’s 32 oz, but the aggregate prices of Heinz 32 increases due to this selective discounting.

**Evaluating Strategic Options for the 1:1 Service Provider**

We next evaluate the optimal strategies for the 1:1 services provider. Since the service provider always gains by selling to either Heinz or Hunt’s, the price it can charge from a given client is the difference in profits of the client in the particular scenario being evaluated, relative to the scenario when only one of the other clients will receive the targeting service. For example, the price that the vendor can charge from selling to Heinz (denoted as firm 1) exclusively when selling the full purchase history is

\[
P^f_1 = \Pi_1^{10} - \Pi_1^{01} = 74534 - 73260 = 1,274.
\]

Table 9 shows the price that Catalina will charge and its profits (assuming zero costs) in each of the targeting scenarios.

*** Insert Table 9***

It is clear from the table that the profit for the 1:1 service provider is greatest when both Heinz and Hunt’s target using the full purchase history ($1475). Therefore the firm will sell the targeting service to both firms (“whom to sell to?” or the optimal customer strategy), using the full purchase history of 100 weeks available (“what to sell?” or the optimal product strategy) at a price of $1,440 to Heinz and $35 to Hunts (“for how much to sell?” or the optimal pricing strategy).

The results suggest that the total profits for the 1:1 marketing services vendor using merely last visit/last purchase based 1:1 targeting is small compared to the profits obtained from using the full history. For example with both firms targeting, the 1:1 vendor makes only $21 in profits from last visit based targeting, whereas it makes $1475 from full visit history based targeting. Another interesting aspect of the results is that while most of the profits for the 1:1 marketing service firm comes from Heinz, offering the service to Hunt’s (even for free) can increase the price that can be obtained from Heinz. This is because of the positive externality for Heinz when Hunt’s uses the service. Heinz profits increase by $1274 when it alone uses the service, but if Hunt’s also uses the service, Heinz profits increase by $1440.

Thus in this category, Catalina would maximize profits by selling its service on a non-exclusive basis to both vendors. It should reevaluate its current strategy of offering the service to only one firm. Further, as we increase the length of purchase data even up to 100 weeks, the profitability of downstream clients continues to increase. Thus restricting the data used for
targeting to 65 weeks is sub-optimal. Specifically, Catalina can improve its profits by increasing the data used from 65 weeks to 100 weeks by 16%. The main reason is that in infrequently purchased categories such as ketchup, the information obtained from purchases over 65 weeks of data is not that large (the median number of purchases in 65 weeks is five). Catalina can improve its profitability by increasing the length of purchase history used in targeting. As data storage continues to become cheaper, this should be technologically feasible.

The Retailer’s Perspective on 1:1 Marketing Services

The retailer is the point of purchase, the place where the consumer purchase data are collected, where customized coupons are printed and delivered and where the coupons are redeemed. The retail loyalty card is most often the means of identifying the consumer and the coupons are usually redeemable only in the same retail chain where purchases are made. Hence a plausible scenario is one where a retailer takes over the role of the 1:1 services provider. A second question of interest is what the value of targeting services will be to a retailer who does not have the targeting infrastructure and whether a firm like Catalina can benefit from providing the service to retailers. We therefore examine the roles of the retailer as both a 1:1 service provider and as a client of a 1:1 service provider.

Retailer as a 1:1 Service Provider

The retailer has two sources of increased profits as a 1:1 service provider; first from the sales of the 1:1 service, but second from the more efficient sales of goods (ketchup) at the retail store. Table 10 reports these two sources of profits. The profit increase from both sources is greatest when both manufacturers target using full history. Retailer profits from sales of ketchup increase by $1,133 while profits from sales of 1:1 services increases by $1,475.

*** Insert Table 10***

Since the retailer profits from sales of ketchup also go up when manufacturers target, the retailer could forgo some proportion of its profits from the 1:1 services business in order to benefit from increase in ketchup profits due to targeting. This provides a compelling economic rationale for why retailers cooperate with Catalina, especially when they do not have the technological infrastructure for targeting. The analysis also implies that retailers could be formidable competitors to a company like Catalina, not only because such retailers may
withdraw themselves from the 1:1 targeting services network (such as the ‘Catalina Marketing Network’) but also because they can price their targeting services more aggressively than a ‘pure’ targeting services provider such as Catalina.\(^{19}\) However, there are two main disadvantages for retailers in entering the 1:1 service business. First, Catalina has patented several aspects of the personalization technology. Second, while a firm like Catalina can provide manufacturers with one-stop shopping for 1:1 coupon services across the country, retailers can provide the 1:1 service only at their chain. Hence manufacturers will have to negotiate for the targeting services with multiple retailers if the retailer provided the services. In fact, in the retail industry, there is other evidence that manufacturers appreciate the benefits of one-stop shopping. For example, News America, a division of News Corp. currently owns the rights to contract out in-store feature and display advertising at about 35,000 food, drug and mass merchandisers nationwide with revenues estimated around $300 million (Neff 2006).

**Retailer as a 1:1 Services Client**

If Catalina provides the 1:1 targeting service to retailers, then retailer profits with full history increases by about 1.88%, suggesting that targeting services to retailers can be an important source of revenue for Catalina. Yet, Catalina’s revenues from retail targeting services is currently only about 9% of its revenues, compared to manufacturer targeting services which account for 53% of revenues.

At first sight, it is surprising that Catalina has not taken advantage of this potential revenue stream. A plausible reason for why Catalina has not aggressively marketed the service to retailers is that, given that retailers are the source of the data, it may be hard for Catalina to extract the surplus created by targeting from retailers. Therefore the prices that Catalina can charge from retailers cannot be as high as those from manufacturers. It also raises broad interesting questions about the property rights with respect to the data and how profits from the use of data should be shared. These issues require more detailed examination in future work.

---

\(^{19}\) In personal conversations with an official at leading retailer who wishes to remain anonymous, we learnt that the retailer provides targeting services informally (for free) to manufacturers.
6. Conclusion

The potential for 1:1 marketing has been growing due to advances in data collection and analysis technologies as well as advertising and promotion delivery technologies. In contrast to extant research on this topic that has an “engineering” orientation, this paper develops an empirical approach to answer strategic questions of interest to 1:1 marketing service providers.

Our analysis enabled us to obtain interesting substantive insights of interest to a 1:1 marketing service provider such as Catalina. First, as discussed in the introduction, Catalina is currently re-evaluating its policy of offering targeting services on an exclusive basis to manufacturers. Given the reservations expressed in the theoretical literature about the negative externalities induced by competitive targeting, Catalina indeed needs to be careful in shifting from its extant policy of selling its targeted couponing services only on an exclusive basis. Our analysis shows that in the category we analyze, Catalina can increase its profits by selling to multiple manufacturers. By performing such an analysis on a category-by-category basis, Catalina can identify categories in which it can improve profits by changing its exclusive selling policy.

Second, we offer the insight that the retailer is likely to be a potent competitor to Catalina. Ginocchio, Chesler and Clark (2005) suggest that a major threat to Catalina’s growth is the growing market share of Wal-Mart in groceries. Since Wal-Mart does not offer targeted coupons and is not part of Catalina’s network, this can hamper Catalina’s growth. According to the report, a second major threat is from Valassis Communications (currently in the business of offering coupons in free standing inserts) which is considering entry into Catalina’s targeted couponing business. The report however suggests that Valassis will find it difficult to replicate Catalina’s success given Catalina’s strong relationship with retailers.

Our analysis suggests that that the major threat to Catalina may not be from Wal-Mart or Valassis, but large retailers themselves, because they can effectively subsidize the price of the 1:1 marketing service because it makes considerable increases in its retail profits due to 1:1 marketing. This threat should be salient given that many retailers (e.g., Tesco in U.K., Kroger in U.S.) are developing their own technologies for offering 1:1 coupons to customers. Indeed the retailer might be the most powerful potential competitor to Catalina in the future.

20 Senior managers at certain leading supermarket chains have stated in discussions with us that they offer targeted coupon services for free to all their manufacturers, while some other retailers charge for the service.
What would happen if there is competition among 1:1 service providers either because the retailer entered the market or if the retailer supplied the data to multiple 1:1 service providers? In such a scenario, a syndication strategy by both 1:1 service providers would not be optimal because neither firm would make any profit given that they would sell homogeneous goods. An exclusive strategy where they sell to different downstream clients is likely to be optimal, since it would create product differentiation.

Finally, we find that Catalina can benefit from increasing the length of purchase history it uses in its targeting services, from the current self-imposed limit of 65 weeks. Even if storage costs are a reason for the current limit of length of purchase history used, the declining costs of storage and computing speeds should make it possible for Catalina to increase the length of history used for 1:1 marketing in the future profitably.

There are a number of ways in which this research can be extended. First, it would be useful to investigate the robustness of our results across multiple categories. We chose the ketchup category to compare our results against Besanko, Dube and Gupta (2003). While the gains from targeting in the ketchup category are low, a Catalina executive told us that they expect substantially higher gains in categories such as snack foods where there is also potential for category expansion in profits due to targeting.

We can expand upon the nature of personalization data used for targeting. Since we did not find demographics to be useful, we treat “purchase history length” as the proxy for data quality. As discussed, quality may be increased through greater “breadth” of the data by integrating purchase behavior from other categories. Though estimation and optimization is computationally much harder across categories, we believe this is an important area for future work. In general, this approach can identify the potential profitability of cross-selling services.

Future research should investigate the impact of greater flexibility in couponing and pricing approaches offered by the 1:1 service provider. In this paper, we follow previous research (Rossi, McCulloch and Allenby 1996, Besanko, Dube and Gupta 2003) in assuming that coupons are valid only for the week of issue. In practice, coupons are valid for multiple weeks and consumers can time when they would use the coupon; firms would then have to account for such dynamic behavior by consumer in issuing the coupon. Modeling timing of coupon redemption therefore requires empirically modeling dynamics and forward looking behavior on both the consumer side (e.g., Gonul and Srinivasan 1996) and firm side (e.g., Gonul and Shi 1998). We
leave this as an interesting area for future research. Also we model the upper threshold of the fee that Catalina can charge manufacturers, given our objective of identifying the best strategy for a 1:1 service provider. This is also consistent with the two part-pricing which Catalina currently uses where the fixed price for the service varies considerably across categories. Nevertheless, a systematic investigation of alternative pricing schemes based on the number and value of coupons issued or redeemed would be an interesting problem for future research.

Finally, we hope that the approach used in this paper will inspire additional research to facilitate decision making in other 1:1 marketing contexts such as in durable goods markets, financial services, catalog marketing and targeted advertising. In the contexts of durable goods or financial services, there will be shorter purchase histories, but greater information across categories that can be used for 1:1 marketing. In the context of targeted advertising services, the empirical model needs to calibrate the impact of advertising (rather than couponing) on consumer purchasing decisions. One can also use the analytical approach used in this paper to domains other than 1:1 marketing. For example one could analyze the optimal licensing/selling of a patented innovation (e.g., Katz and Shapiro 1985). Licensing of an innovation to multiple downstream firms may create greater competition downstream and thus reduce the total value of the innovation relative to the strategy of exclusively selling the patent to one firm. In short, while appropriate changes are needed for the model to deal with institutional details appropriate for each context, the general framework of understanding the tradeoffs involved in improving quality and selling to exclusive/multiple clients will continue to be relevant. More broadly, we hope that this approach will spawn similar complementary research to game theoretic analysis on other marketing institutions to help decision makers and managers obtain empirically driven answers to their business strategy questions.
References


Figure 1: Schematic of the Market

- Personalization Supplier (e.g., Catalina)
  - What to Offer? (Product)
  - Whom to Offer? (Customer)
  - At What Prices?
  - Manufacturer 1 (Brand 1)
  - Manufacturer 2 (Brand 2)
  - Retailer (Store Brand)
  - Coupons for Customers:
    - Retailer
    - Set Wholesale Prices
    - Set Retail Prices
  - Consumers
Figure 2: Decision Tree and Payoffs

1:1 SP: “What” to Sell?

Last Visit

... Last Purchase

Full History

1:1 SP: “Whom” to Offer?
At What Price?

Offer Mfr 1 at \( P_1^f \)
Offer Mfr 2 at \( P_2^f \)
Offer Both Mfrs at \( P_1^b, P_2^b \)

Mfr 1: Accept/Reject

Mfr 1 Accepts

Mfr 1 Rejects

Mfr 2: Accept/Reject

Mfr 2 Accepts

Mfr 2 Rejects

Mfr 1: Accept/Reject

Mfr 1 Accepts

Mfr 1 Rejects

Neither Mfr Accepts

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 1 Accepts} \\
&P_1^f \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 2 Accepts} \\
&P_2^f \\
&\Pi_2^{10} - P_2^f
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 2 Rejects} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 1 Rejects} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 1 Accepts} \\
&P_1^f \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 2 Rejects} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 1 Rejects} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 1 Accepts} \\
&P_1^f \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Mfr 2 Rejects} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Both Mfrs Accept} \\
&P_1^b + P_2^b \\
&\Pi_1^{11} - P_1^b \\
&\Pi_2^{11} - P_2^b
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Only Mfr 1 Accepts} \\
&P_1^f \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Only Mfr 2 Accepts} \\
&P_2^f \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]

Phase II Payoffs

\[
\begin{align*}
&\text{Neither Mfr Accepts} \\
&0 \\
&\Pi_1^{10} - P_1^f \\
&\Pi_2^{10}
\end{align*}
\]
Figure 3a

Last visit used in Segment 1 allocation

Figure 3b

Last purchase used in Segment 1 allocation

Figure 3c

Full History Used in Segment 1 allocation
Figure 4a

Posterior Segment Probabilities of Heinz
Targeted/Non Targeted Households

<table>
<thead>
<tr>
<th>Segments</th>
<th>Average Posterior Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price sensitive Heinz 32 loyals (0.47)</td>
<td>0.32</td>
</tr>
<tr>
<td>Light users, Heinz 28 loyals (0.24)</td>
<td>0.01</td>
</tr>
<tr>
<td>Price sensitive heavy users (0.29)</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Heinz 32 targets (32%)  Heinz 32 does not targets (68%)

Figure 4b

Posterior Segment Probabilities of Hunt’s
Targeted/Non Targeted Households

<table>
<thead>
<tr>
<th>Segments</th>
<th>Average Posterior Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price sensitive Heinz 32 loyals (0.47)</td>
<td>0.12</td>
</tr>
<tr>
<td>Light users, Heinz 28 loyals (0.24)</td>
<td>0.0</td>
</tr>
<tr>
<td>Price sensitive heavy users (0.29)</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Hunt’s 32 targets (9%)  Hunt’s 32 does not target (91%)
<table>
<thead>
<tr>
<th>Company/Division</th>
<th>2004 Revenue ($ mil.)</th>
<th>% of total company revenue</th>
<th>2004 Market Cap ($ mil.)</th>
<th>Client profile, Client examples</th>
<th>Revenue Growth rate</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catalina Marketing, Inc</td>
<td>470</td>
<td>100%</td>
<td>1400</td>
<td>Manufacturers of packaged goods, grocery retailers e.g. Nestle, Safeway</td>
<td>8% p.a. over 2000-2004</td>
<td>Proprietary technology at point of purchase in grocery and pharma retailers to track customer transactions and deliver customized coupons. Tracks over 250 million transactions per week across more than 21,000 supermarkets worldwide, tracks purchase history of over 100 million households in U.S. Delivers more than 4.5 billion customized promotional messages.</td>
</tr>
<tr>
<td>Doubleclick, Inc (Abacus B2C division)</td>
<td>105</td>
<td>35%</td>
<td>984</td>
<td>Catalog merchants, e.g., LL Bean,Sharper Image</td>
<td>10%(2004), 15.1% (2003)</td>
<td>Consolidates the input from 1,550 catalog, online, and retail merchants into a single database. Data on over 4.4 billion transactions from catalog call-centers, websites, and retail stores, made by over 90 million households, with household purchase data stretching back 5 years.</td>
</tr>
<tr>
<td>Experian’s z-24 Division</td>
<td>501</td>
<td>23%</td>
<td>NA</td>
<td>Catalog companies, e.g., Boston Proper, JJill, Retailers, non-profits</td>
<td>6% p.a. over 2001-2004</td>
<td>The Z-24 database is similar to Abacus. Data from over 755 catalogs with 38 million households that have purchased over the last two months. Experian is also a player in B2B targeting with BizInsight’s database of more than 15 million U.S. based businesses.</td>
</tr>
<tr>
<td>VT &amp;NH’s Direct Marketing Group’s I-Behavior</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Catalog companies, e.g., Gardener’s Supply, Vermont Country Store</td>
<td>NA</td>
<td>Competitor to Abacus and Z-24, but uses transactional data at the SKU level (in contrast to Abacus and Z-24 which uses catalog level data). 1000+ contributors, mostly medium sized catalog companies, data on 103 million consumers, 89 million households.</td>
</tr>
<tr>
<td>Harte Hanks’ Direct Marketing Division</td>
<td>641</td>
<td>62%</td>
<td>2448</td>
<td>Retailers, finance sector, pharmaceuticals, telecom &amp; high-tech</td>
<td>9% (2004), 2% (2003)</td>
<td>Specializes in providing targeting solutions in automotive, consumer products, financial services, insurance, high tech, pharma, retail and telecom. Provides suite of services from constructing the database (Trillium Software System), accessing the data (Allink™ suite, inTouch), in-house data analytics, application and execution of campaigns.</td>
</tr>
<tr>
<td>Cool Savings, Inc</td>
<td>38</td>
<td>100%</td>
<td>NA</td>
<td>Retailers, packaged goods manufacturers,e.g. Unilever, Land O’ Lakes, Best Buy</td>
<td>20% p.a. over 2001-2004</td>
<td>Online marketer maintains a network of Web sites featuring a variety of special offers and savings on a range of goods and services from its advertisers. Also offers lead generation, e-mail marketing, and loyalty programs for more than 1,000 companies in retail, packaged goods, and media industries. Uses demographic information from its 20 million visitors to help its advertisers design targeted marketing campaigns and promotions.</td>
</tr>
</tbody>
</table>
### Table 2: Descriptive Statistics for Ketchup Data

<table>
<thead>
<tr>
<th></th>
<th>Conditional Brand share</th>
<th>Price ($/10 oz)</th>
<th>Feature</th>
<th>Display</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heinz 32 oz</td>
<td>37%</td>
<td>0.41</td>
<td>0.07</td>
<td>0.11</td>
</tr>
<tr>
<td>Hunt’s 32 oz</td>
<td>13%</td>
<td>0.42</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Heinz 28 oz</td>
<td>22%</td>
<td>0.50</td>
<td>0.04</td>
<td>0.09</td>
</tr>
<tr>
<td>Store Brand 32 oz</td>
<td>28%</td>
<td>0.28</td>
<td>0.12</td>
<td>0.12</td>
</tr>
</tbody>
</table>

### Table 3: Demand Model Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Segment 1 (47%)</th>
<th>Segment 2 (24%)</th>
<th>Segment 3 (29%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std Err)</td>
<td>Estimate (Std Err)</td>
<td>Estimate (Std Err)</td>
</tr>
<tr>
<td>Heinz 32 oz</td>
<td>1.90*** (0.47)</td>
<td>-2.28** (0.13)</td>
<td>1.89*** (0.45)</td>
</tr>
<tr>
<td>Hunt’s 32 oz</td>
<td>0.60 (0.56)</td>
<td>-3.33*** (0.16)</td>
<td>3.14*** (0.50)</td>
</tr>
<tr>
<td>Heinz 28 oz</td>
<td>0.80 (0.62)</td>
<td>-1.85*** (0.15)</td>
<td>2.95*** (0.59)</td>
</tr>
<tr>
<td>SB 32 oz</td>
<td>-0.50 (0.43)</td>
<td>-5.66*** (0.26)</td>
<td>1.72*** (0.35)</td>
</tr>
<tr>
<td>Price</td>
<td>-13.23*** (1.25)</td>
<td>-2.89*** (0.19)</td>
<td>-16.91*** (1.22)</td>
</tr>
<tr>
<td>Feature</td>
<td>0.90*** (0.14)</td>
<td>0.74*** (0.22)</td>
<td>-0.11 (0.12)</td>
</tr>
<tr>
<td>Display</td>
<td>0.51*** (0.14)</td>
<td>0.33* (0.19)</td>
<td>0.07 (0.12)</td>
</tr>
<tr>
<td>Inventory</td>
<td>-3.19*** (0.35)</td>
<td>-1.09*** (0.10)</td>
<td>-0.16 (0.27)</td>
</tr>
<tr>
<td>State Dependence</td>
<td>0.62*** (0.18)</td>
<td>1.42*** (0.18)</td>
<td>1.24*** (0.17)</td>
</tr>
<tr>
<td>Price Residual (Heinz 32)</td>
<td>0.50*** (0.18)</td>
<td>-0.04 (0.20)</td>
<td>-0.37** (0.20)</td>
</tr>
<tr>
<td>Price Residual (Hunt’s 32)</td>
<td>0.29 (0.40)</td>
<td>0.07 (0.66)</td>
<td>1.70*** (0.42)</td>
</tr>
<tr>
<td>Price Residual (Heinz 28)</td>
<td>-0.21 (0.29)</td>
<td>0.10 (0.13)</td>
<td>0.11 (0.26)</td>
</tr>
<tr>
<td>Price Residual (SB 32)</td>
<td>0.41 (0.44)</td>
<td>2.36 (1.53)</td>
<td>1.04*** (0.31)</td>
</tr>
</tbody>
</table>

***p<0.01 , **p<0.05,* p< 0.1
Table 4: Mean Price Elasticities for the 3 Segment Model

<table>
<thead>
<tr>
<th>Change in Price</th>
<th>Change in Share</th>
<th>Heinz 32</th>
<th>Hunt’s 32</th>
<th>Heinz 28</th>
<th>SB 32</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heinz 32</td>
<td>-3.52</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Hunt’s 32</td>
<td>0.03</td>
<td>-5.18</td>
<td>0.02</td>
<td>0.09</td>
<td></td>
</tr>
<tr>
<td>Heinz 28</td>
<td>0.03</td>
<td>0.03</td>
<td>-2.20</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Store Brand 32</td>
<td>0.03</td>
<td>0.11</td>
<td>0.02</td>
<td>-4.14</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Cost Equation Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate (Std Err)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heinz 32 oz</td>
<td>0.036 (0.072)</td>
</tr>
<tr>
<td>Hunt’s 32 oz</td>
<td>0.088 (0.072)</td>
</tr>
<tr>
<td>Heinz 28 oz</td>
<td>0.038 (0.073)</td>
</tr>
<tr>
<td>SB 32 oz</td>
<td>-0.041 (0.072)</td>
</tr>
<tr>
<td>Tomatoes</td>
<td>0.152* (0.063)</td>
</tr>
</tbody>
</table>

* p < 0.01
Table 6: Incremental Profits from 1:1 Coupons

<table>
<thead>
<tr>
<th>Targeting by</th>
<th>Last Visit</th>
<th>Last Purchase</th>
<th>Full History</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Heinz</td>
<td>Hunt’s</td>
<td>Heinz</td>
</tr>
<tr>
<td></td>
<td></td>
<td>t-stat relative to Last Visit</td>
<td>t-stat relative to Last Visit</td>
</tr>
<tr>
<td>Neither Hunts only</td>
<td>Profits</td>
<td>73,301</td>
<td>73,317</td>
</tr>
<tr>
<td></td>
<td>Profits</td>
<td>4,139</td>
<td>4,139</td>
</tr>
<tr>
<td>% Increase relative to No Targeting</td>
<td>0.02%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>t-stat relative to No Targeting Profits</td>
<td>8.06*</td>
<td>-0.74*</td>
<td>0.79</td>
</tr>
<tr>
<td>Heinz only</td>
<td>Profits</td>
<td>73,304</td>
<td>73,620</td>
</tr>
<tr>
<td>% Increase relative to No Targeting</td>
<td>0.00%</td>
<td>0.43%</td>
<td>0.16%</td>
</tr>
<tr>
<td>t-stat relative to No Targeting Profits</td>
<td>3.43*</td>
<td>37.36*</td>
<td>16.19*</td>
</tr>
<tr>
<td>Heinz &amp; Hunts</td>
<td>Profits</td>
<td>73,338</td>
<td>73,620</td>
</tr>
<tr>
<td>% Increase relative to No Targeting</td>
<td>0.05%</td>
<td>0.44%</td>
<td>0.15%</td>
</tr>
<tr>
<td>t-stat relative to No Targeting Profits</td>
<td>10.94*</td>
<td>37.39*</td>
<td>16.81*</td>
</tr>
</tbody>
</table>

*ns*: not significant

*: $p < 0.01$
### Table 7: Accuracy in Computing Targeting Profits

<table>
<thead>
<tr>
<th></th>
<th>Heinz profits ($)</th>
<th>Hunt’s profits ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No firm targets (aggregate behavior)</td>
<td>66,628</td>
<td>4,116</td>
</tr>
<tr>
<td>No firm targets (true individual behavior)</td>
<td>73,301 (10.02%)</td>
<td>4,139 (0.56%)</td>
</tr>
<tr>
<td>Both firms target with last visit data</td>
<td>73,338 (10.07%)</td>
<td>4,139 (0.56%)</td>
</tr>
<tr>
<td>Both firms target with last purchase data</td>
<td>73,620 (10.49%)</td>
<td>4,145 (0.70%)</td>
</tr>
<tr>
<td>Both firms target with full history data</td>
<td>74,700 (12.12%)</td>
<td>4,174 (1.41%)</td>
</tr>
</tbody>
</table>

### Table 8: Effect of 1:1 Coupons on Shares, Margins and Category Purchase

<table>
<thead>
<tr>
<th></th>
<th>Both target using full history</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Heinz</td>
</tr>
<tr>
<td>Average increase in share</td>
<td>Hz 32: +0.3%</td>
</tr>
<tr>
<td></td>
<td>Hz 28: +0.4%</td>
</tr>
<tr>
<td>Increase in (share weighted) margins</td>
<td>Hz 32: +2.8%</td>
</tr>
<tr>
<td></td>
<td>Hz 28: +0.6%</td>
</tr>
<tr>
<td>Average increase in category purchase</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 9: Price and 1:1 Marketing Services Vendor Profits under Alternative 1:1 Marketing Scenarios

<table>
<thead>
<tr>
<th></th>
<th>Last Visit Based Targeting</th>
<th></th>
<th>Full History Based Targeting</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price for Heinz</td>
<td>Price for Hunt’s</td>
<td>Total Profits</td>
<td>Price for Heinz</td>
</tr>
<tr>
<td>No firm targets</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hunt’s only targets</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Heinz only targets</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1,274</td>
</tr>
<tr>
<td>Both firms target</td>
<td>21</td>
<td>0</td>
<td>21</td>
<td>1,440</td>
</tr>
</tbody>
</table>

Table 10: Incremental Retailer Profits from 1:1 Marketing Services

<table>
<thead>
<tr>
<th></th>
<th>Full History Based Targeting</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profits from Ketchup Profits</td>
<td>Profits from 1:1 Marketing Service</td>
</tr>
<tr>
<td>No firm targets</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hunt’s only targets</td>
<td>1,040</td>
<td>15</td>
</tr>
<tr>
<td>Heinz only targets</td>
<td>0</td>
<td>1,274</td>
</tr>
<tr>
<td>Both firms target</td>
<td>1,133</td>
<td>1,475</td>
</tr>
</tbody>
</table>
Appendix

A. The Pricing Equations

Retailer

From (5), the retailer’s optimization problem is as follows.

\[
\max_{\eta, \ldots, \eta_j} \Pi_{t}^{\text{sv}} = \sum_{j=1}^{N} \sum_{i=1}^{N} \left[ r_{ji}^{\text{sv}} - w_{ji}^{\text{sv}} \right] * \left[ \sum_{k=1}^{K} f^{k} S_{ij}^{k} (r_{ji}^{\text{sv}} - D_{ji}^{\text{sv}}) \right] * M_{t}
\]  

(A1)

For the purposes of the derivation, we drop the superscripts \(x\) and \(y\) indicating whether a manufacturer bought targeting services and the subscript \(t\) that indexes time-period for clarity. These can be included appropriately into the final wholesale and retail margins. Hence the retailer objective is:

\[
\max_{\eta, \ldots, \eta_j} \Pi_{t} = \sum_{j=1}^{N} \left[ r_{j} - w_{j} \right] * \left[ \sum_{k=1}^{K} f^{k} S_{ij}^{k} (r_{j} - D_{ij}) \right] * M_{t}
\]

Taking the derivative of the objective function with respect to the retail prices, the following first order condition for each product \(j\) is:

\[
\sum_{i=1}^{N} \left[ \sum_{m=1}^{J} \left[ r_{j} - w_{j} \right] \frac{\partial S_{ij}^{k} (r_{m} - D_{ij})}{\partial r_{j}} + \sum_{k=1}^{K} f^{k} S_{ij}^{k} (r_{m} - D_{ij}) \right] = 0
\]

where \(w_{j}\) is the wholesale price charged by manufacturer to the retailer for brand \(j\).

Define \(\Theta_{i}\) as the the first derivatives of all the (individual consumers’) shares with respect to all retail prices (retail prices are common across consumers), with element \((j,m) = \frac{\partial S_{im}^{k} (r_{m})}{\partial r_{j}}\)

The retailer first order conditions can then be written in matrix form as:

\[
\sum_{i=1}^{N} \left[ \Theta_{i}^{j} \left[ R - W \right] + S^{j} \right] = 0
\]

where \(R\) is the vector of retail prices and \(W\) is the vector of wholesale prices (which are common across all consumers) and \(S^{j}\) is the vector of shares for each consumer ‘\(i\)’ over all the brands:

\[
R = \begin{bmatrix} r_{1} \\ \vdots \\ r_{j} \end{bmatrix}, \quad W = \begin{bmatrix} w_{1} \\ \vdots \\ w_{j} \end{bmatrix}, \quad S^{j} = \begin{bmatrix} S_{1}^{j} \\ \vdots \\ S_{j}^{j} \end{bmatrix}
\]

The vector of retail margins \( [ R - W ] \) is obtained by inverting the above matrix equation:
\[ R - W = \left[ \sum_{i=1}^{N} \Theta_{ir} \right]^{-1} \left[ \sum_{i=1}^{N} S_i \right] \quad (A3) \]

Retail Margin

where the shares are:

\[ S_i = \sum_{k=1}^{K} f^k S_i^k \]

and the individual specific share derivative matrix with respect to retailer prices is:

\[ \Theta_{ir} = \begin{bmatrix} \frac{\partial S_{i1}}{\partial p_1} & \frac{\partial S_{i2}}{\partial p_1} & \ldots & \frac{\partial S_{ij}}{\partial p_1} \\ \frac{\partial S_{i1}}{\partial p_j} & \frac{\partial S_{i2}}{\partial p_j} & \ldots & \frac{\partial S_{ij}}{\partial p_j} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{i1}}{\partial p_j} & \frac{\partial S_{i2}}{\partial p_j} & \ldots & \frac{\partial S_{ij}}{\partial p_j} \end{bmatrix}_{j \neq j} \quad (A4) \]

\[
\begin{bmatrix}
\sum_{k=1}^{K} f^k \left[ xS_i^k [1 - S_i^k] \right] \\
\sum_{k=1}^{K} f^k \left[ -xS_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ -xS_i^k S_i^k \right] \\
\sum_{k=1}^{K} f^k \left[ -S_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ -S_i^k S_i^k \right] \\
\sum_{k=1}^{K} f^k \left[ -xS_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ xS_i^k [1 - S_i^k] \right] \\
\sum_{k=1}^{K} f^k \left[ -S_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ -S_i^k S_i^k \right] \\
\sum_{k=1}^{K} f^k \left[ xS_i^k [1 - S_i^k] \right] \\
\sum_{k=1}^{K} f^k \left[ -xS_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ -S_i^k S_i^k \right] \\
\sum_{k=1}^{K} f^k \left[ -xS_i^k S_i^k \right] \\
\vdots \\
\sum_{k=1}^{K} f^k \left[ xS_i^k [1 - S_i^k] \right] \\
\end{bmatrix}_{j \neq j}
\]

Therefore the retail price is given by

\[ R = W - \left[ \sum_{i=1}^{N} \Theta_{ir} \right]^{-1} \left[ \sum_{i=1}^{N} S_i \right] \quad (A5) \]

Manufacturer

A manufacturer ‘\( m \)’ offering a subset \( \mathbb{N}_m \) of brands in the market sets the wholesale price \( w^w_{ji} \) (where \( j \in \mathbb{N}_m \)) and the coupon face values to individual households \( (D^w_{ij})_i \) so as to maximize the manufacturer’s profits. A manufacturer who has not been sold the 1:1 marketing service will have coupon face values set to zero. The manufacturer takes into account the knowledge that retailer prices \( (r^w_{ji})_i \) will be set taking into account the wholesale prices and the coupon face values that have been issued to individual households.
\[
\Pi_{m}^{xy} = \sum_{j \in \mathcal{N}_{m}} \sum_{i=1}^{N} [w_{ji}^{xy} - D_{ij}^{xy} - c_{jt}] \left[ S_{ijt}(r_{jt}^{xy}(w_{ji}^{xy}, D_{ij}^{xy}) - D_{ij}^{xy}) \right] * M_{t}
\] (A6)

where \( c_{jt} \) is the marginal cost of the manufacturer for brand \( j \) in period \( t \), and \( S_{ijt}(r_{jt}^{xy}(w_{ji}^{xy}, D_{ij}^{xy}) - D_{ij}^{xy}) \) is the probability of household \( i \), buying brand \( j \) in period \( t \) given the decisions of manufacturers 1 (denoted by \( x \)) and 2 (denoted by \( y \)) to purchase the purchase history data, and \( M_{t} \) is the total size of the market in period \( t \). We present the first order conditions for the manufacturer dropping the \( x, y \) superscripts and the ‘\( t \)’ subscript and writing retail price as \( r_{j} \) (not as \( r_{j}(w_{j},D_{j}) \)) for clarity.

We write \( w_{ij} = w_{j} - D_{ij} \) since the manufacturer sets both the wholesale price and the individual coupon face values to maximize profit. As discussed earlier, even though the manufacturer sets the wholesale price and Catalina sets the coupon face value, analytically it does not matter whether we make this distinction. The first order condition with respect to \( w_{ij} \) is:

\[
\sum_{i=1}^{N} \sum_{j \in \mathcal{N}_{m}} \left[ (w_{ij} - c_{jt}) \left[ dS_{ij}(r_{j} - D_{j}) + S_{ij}(r_{j} - D_{j}) \right] \right] = 0
\] (A7)

Define \( \Theta^{i}_{W} \) for each individual consumer such that it contains the first derivatives of all the (individual consumers’) shares with respect to all wholesale prices (wholesale prices are common across consumers), with element \((j,m) = \frac{\partial S_{im}(r_{m} - D_{m})}{\partial w_{ij}} \). To account for the set of brands owned by the same manufacturer, define the manufacturer’s ownership matrix \( O_{w} \) such that element \((j,m) \) is equal to one if the manufacturer who sells brand \( j \) also sells brand \( m \), and zero otherwise. The manufacturer’s first order condition can then be written in matrix form as:

\[
\sum_{i=1}^{N} \left[ [O_{w} \bullet \Theta^{i}_{W}][W_{i} - C] + S^{i} \right] = 0
\] (A8)

where \([O_{w} \bullet \Theta^{i}_{W}] \) is the element by element multiplication of the two matrices, \( W_{i} \) is the vector of wholesale prices less the individual coupon values, \( C \) is the vector of marginal costs of the manufacturer (\( C \) is common across all consumers), and \( S^{i} \) is the vector of shares for each consumer \( i \).
From the manufacturer first order conditions, we can write the manufacturer margin from a particular household $i$ $[W_i - C]$ as follows:

$$[W_i - C] = [O_w \cdot \Theta'_w]^{-1} \cdot [-S']$$ (A9)

The share derivatives with respect to wholesale matrix $\Theta'_w$ need to be calculated. As mentioned earlier, the manufacturer response matrix has the elements $(j,m) = \frac{\partial S_m}{\partial W_j} (r_m - D_m)$. Define the Jacobian matrix of derivatives of all retail prices to all wholesale prices (for consumer ‘i’) as $\Delta_{rw}^i$, with the element $(j,x) = \frac{dr_i(W)}{dw_j}$. Then $\Theta'_w$ can be re-written as:

$$\Theta'_w = \Delta_{rw}^i \Theta'_R$$ (A10)

In the Manufacturer Stackelberg game, manufacturers anticipate how the retailer will respond to changes in wholesale prices and use these reactions when setting wholesale prices. We can solve for the retail reactions $\frac{dr_i(W)}{dw_j}$ by taking the total derivative of the retailer’s first order condition with respect to the retail price $r_j$ and the wholesale price $w_j$:

$$\Psi_{w^i}^* = \begin{bmatrix} \frac{dr_1}{dw_1} & \frac{dr_1}{dw_2} & \cdots & \frac{dr_1}{dw_J} \\ \frac{dr_2}{dw_1} & \frac{dr_2}{dw_2} & \cdots & \frac{dr_2}{dw_J} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{dr_J}{dw_1} & \frac{dr_J}{dw_2} & \cdots & \frac{dr_J}{dw_J} \end{bmatrix}_{JxJ} \cdot \begin{bmatrix} \frac{\partial S_1^i}{\partial r_1} & \frac{\partial S_2^i}{\partial r_1} & \cdots & \frac{\partial S_J^i}{\partial r_1} \\ \frac{\partial S_1^i}{\partial r} & \frac{\partial S_2^i}{\partial r} & \cdots & \frac{\partial S_J^i}{\partial r} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_1^i}{\partial r_J} & \frac{\partial S_2^i}{\partial r_J} & \cdots & \frac{\partial S_J^i}{\partial r_J} \end{bmatrix}_{JxJ}$$

where

---

22 Villas Boas and Hellerstein (2006) discuss two conditions to assure the invertibility of the Jacobian matrix: (1) additive separability of costs across products for retailer and manufacturer and (2) no interaction between manufacturer and retailer costs. Since these assumptions are maintained in our paper, the Jacobian is invertible.
\[
\Psi'_w = \left[ \begin{array}{cccc}
2 \frac{\partial S_i^j}{\partial r_i} + \sum_{m=1}^{j} [r_m - w_m] \frac{\partial^2 S_i^j_m}{\partial r_i^2} & \cdots & \frac{\partial S_i^j}{\partial r_j} + \sum_{m=1}^{j} [r_m - w_m] \frac{\partial^2 S_i^j_m}{\partial r_j r_i} \\
\vdots & \ddots & \ddots & \vdots \\
\frac{\partial S_i^j}{\partial r_j} + \sum_{m=1}^{j} [r_m - w_m] \frac{\partial^2 S_i^j_m}{\partial r_j r_i} & \cdots & 2 \frac{\partial S_i^j}{\partial r_j} + \sum_{m=1}^{j} [r_m - w_m] \frac{\partial^2 S_i^j_m}{\partial r_j^2} 
\end{array} \right]_{jj} 
\]

(A11)

The second derivatives are obtained for these relationships of \(a,b,c\) (where there is an equality sign, the index \(a\) will be preferred to \(c\) or \(b\) if \(a\) is in the equality, and \(b\) will be preferred to \(c\) if \(b\) is in the equality). :

\[
\alpha^2 * S_a^i *[1 - S_a^i] *[1 - 2 * S_a^i] \quad a = c = b \\
2 * \alpha * S_a^i * S_b^i * S_c^i \quad a \neq c \neq b \\
\frac{\partial^2 S_a^j}{\partial r_c r_b} = \alpha^2 * S_a^i * S_b^i * [2 * S_a^i - 1] \quad a = c \neq b \\
\quad \alpha^2 * S_a^i * S_c^i * [2 * S_a^i - 1] \quad a = b \neq c \\
\quad \alpha^2 * S_b^i * S_c^i * [2 * S_b^i - 1] \quad a \neq c = b
\]

(A12)

Writing the total derivative of the retailer’s first order condition in matrix form:

\[
\Psi'_w * [\Delta'_w]^T = \Theta_R^i 
\]

where \([\Delta'_w]^T\) is the transpose of the matrix \(\Delta'_w\). Therefore \(\Delta'_w\) is obtained as:

\[
\Delta'_w = \left[ [\Psi'_w]^T * \Theta_R^i \right]^T
\]

(A13)

The wholesale price to the retailer is given by \(w_j = \max_i w_{ij}\) and the individual specific discount is given by \(D_{ij} = w_{jt} - w_{ij}\).

**B. Endogeneity Correction**

We correct for price endogeneity using the control function approach developed in Petrin and Train (2004). The control function approach has similarities to Rivers and Vuong (1988) and Villas Boas and Winer (1999). The ‘control function’ approach (Hausman 1978) uses extra variables to control for the part of the unobserved component of demand that is correlated with price. In principle, the control functions are constructed using as arguments the differences between observed prices and the predicted prices which are arrived at using all the relevant demand and supply variables observed by the econometrician.

Consider the utility equation:
and rewrite it incorporating the control function as:

$$u_{ijt} = X_{ijt} \beta - r_{jt} \alpha + \tilde{\xi}_{jt} + \varepsilon_{ijt}$$  \hspace{1cm} (B1)

where \( \tilde{\xi}_{jt} \) is the function that controls for the correlation of the unobserved component \( \xi_{jt} \) with the price \( r_{jt} \). \( \mu_{jt} \) are control variables used in such a correction, and \( \omega \) are the coefficients for \( \mu_{jt} \). Let the redefined unobserved component be \( \eta_{jt} = [\tilde{\xi}_{jt} - f(\mu_{jt}; \omega)] \). If the function \( f(\mu_{jt}; \omega) \) could be constructed and added to the utility function, it is clear from equation (B2) that the resulting random component \( \eta_{jt} + \varepsilon_{ijt} \) would no longer be correlated with price (by construction), and the estimates obtained would be corrected for price endogeneity. Petrin and Train (2004) show that (under a wide range of conditions) the control function \( f(\mu_{jt}; \omega) \) is linear in the price residuals of a regression of price on its primitives. In our context, we estimate a regression of prices against factor costs as follows:

$$r = \kappa_j + \tilde{\xi} * B_i + \mu_{jt}$$

where \( B_i \) are the factor prices, \( \kappa_j \) are brand specific intercepts and \( \mu_{jt} \) are the residuals from this regression. Thus \( f(\mu_{jt}; \omega) = \omega \mu_{jt} \), and we write equation (B2) as:

$$u_{ijt} = X_{ijt} \beta - r_{jt} \alpha + \omega \mu_{jt} + \eta_{jt} + \varepsilon_{ijt}$$  \hspace{1cm} (B3)

This utility equation (B3) is used in estimating the latent class model rather than equation (1) of the text to perform the endogeneity correction. Different specifications can be used for \( \omega \) (Petrin and Train 2004 pages 25-26), and we present the results where \( \omega \) is segment-specific, i.e.,

\[ \omega_k \]