

## **Optimal Marketing Strategies for a Customer Data Intermediary\***

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## Optimal Marketing Strategies for a Customer Data Intermediary

### Abstract

Advances in data collection and storage technologies have given rise to the “*customer data intermediary*” (CDI)—a firm that collects customer data to offer customer-specific marketing services to marketers. With widespread adoption of customer relationship management (CRM) and one-to-one (1:1) marketing, the demand for such services continues to grow. Extant empirical research using customer data for CRM and 1:1 marketing tends to have an *engineering* emphasis; they focus on developing analysis techniques to optimally implement CRM and 1:1 marketing; i.e., the technology for the CDI. In contrast, this paper focuses on *marketing strategy* issues faced by the intermediary, *given the availability of the technology* to implement such services. Specifically, we develop an empirical framework to evaluate the optimal customer (exclusive/non-exclusive), product (quality or accuracy of the 1:1 customization) and pricing strategy for a CDI. We illustrate the framework for one type of CDI - a 1:1 coupon service firm catering to grocery manufacturers using household purchase history data from the ketchup market. We find that selling on a *non-exclusive* basis using the *maximum available purchase history* data is the most profitable strategy for the CDI in the particular market. We also evaluate the potential impact of retailers entering the 1:1 coupon service business. Since 1:1 marketing can increase the retailer’s profits from goods sold, it is optimal for the retailer to undercut the prices of a pure play CDI offering 1:1 coupon services.

**Keywords:** Customer Information, CRM, One-to-One Marketing, Database Marketing, Couponing, Price Discrimination, Competition, Marketing Channels, Customer Data Intermediaries.

## Optimal Marketing Strategies for a Customer Data Intermediary

In recent years, a new type of firm— “customer data intermediaries” (CDI)— firms that specialize in collecting customer behavior and demographic data and offer customer-specific marketing services has emerged. For example, 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.<sup>1</sup> 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.<sup>2</sup>

With widespread adoption of customer relationship management (CRM) and one-to-one (1:1) marketing, the demand for CDI services continues to grow. Table 1 lists some of the major players in the CDI 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\*\*\*\*

Advances in data collection, data storage and customer-specific promotion delivery technologies fuel the rise and growth of customer data intermediaries. 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, while 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. Further, advances in promotion delivery technologies to individuals

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<sup>1</sup> 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).

<sup>2</sup> 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.

(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.

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 customer databases to improve marketing effectiveness. From the CDI perspective, this research develops the technology to create their customer-specific marketing services.

In contrast to such “engineering” research, this paper focuses on “marketing” problems facing the CDI. Specifically, we ask the research question: conditional on the availability of the 1:1 technology, what is the optimal customer and product strategy for the CDI? And conditional on the customer and product strategy, what price should the CDI charge for the service?

In practice, there is considerable diversity in the customer and product strategies of CDIs. Some sell their 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.<sup>3</sup> In contrast, Abacus and i-Behavior™ sell on a non-exclusive basis to any catalog marketer or specialty retailer who requests their services.

CDIs 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.<sup>4</sup> In contrast to Catalina, Abacus continues to expand the accuracy of its database. Abacus pools data from over 1550 catalog marketers/specialty retailers on over 90

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<sup>3</sup> 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.

<sup>4</sup> 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.

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.<sup>5</sup>

It is possible that the existing strategies of an intermediary 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 customer data intermediaries benefit from changing their current customer and product strategies? Currently, there is little research to guide them on what the optimal strategy should be. In this paper, we offer an empirical framework to help an intermediary 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. Such an approach would complement the theoretical analysis of targeted advertising by Iyer, Villas-Boas and Soberman (2005).

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<sup>5</sup> 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 DoubleClick.

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 \$1.3 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 customer purchase history data used for 1:1 coupon services. Catalina’s intermediary business model is predicated on cooperation from the retailer. A natural question that arises is: What if the retailer chooses to dis-intermediate Catalina and offer the service itself? 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 1:1 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 CDI 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; Iyengar, Ansari and Gupta 2003); 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.<sup>6</sup>

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<sup>6</sup> 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 CDI are intertwined and the empirical question of what is the optimal strategy for a particular CDI 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. 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 CDI.

### **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

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

based pricing. Using similar models, Thisse 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. Shin and Sudhir (2006) however develop a model where customers are distinguished on the basis of their profitability (using the 80/20 rule) and behavior based pricing does not lead to a prisoner's dilemma.

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. Zhang and Krishnamurthi (2004) empirically study customized pricing in online stores.

The paper is also related to the theoretical literature on information suppliers and investments in information. Iyer and Soberman (2000) study how the marketing strategies of an information supplier are affected by downstream competition between firms who use product modification information. In a similar spirit, this paper analyzes how the marketing strategies of the CDI are affected by how grocery manufacturers use the service downstream for 1:1 couponing. But the model for how the data is used downstream is very different in the two papers. Further, our analysis is empirical and therefore requires modeling several specific features of the market (e.g., strategic interactions between manufacturers and retailers) that can be abstracted away from a theoretical analysis.

Other related theoretical papers that address some issues in our paper are Chen and Iyer (2002) and Liu and Zhang (2006). Chen and Iyer (2002) study how firms differentially invest in customer addressability to avoid the negative effects of downstream competition. Liu and Zhang (2006) theoretically investigate the interaction between manufacturers and retailers in the presence of personalized pricing. Even though retailer's profits are lower in the presence of personalized pricing either by the manufacturer or the retailer, the retailer prefers to use personalized retail pricing in order to deter direct selling and personalized pricing by manufacturers, which leads to even worse outcomes for the retailer.

### **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 CDI (e.g., Catalina) (2) the manufacturers (3) a retailer and (4) consumers.

\*\*\* Insert Figure 1\*\*\*

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 (CDI) 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 (CDI) 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<sup>®</sup> program and (3) Full Purchase History, along the lines of what Catalina uses in its Catalina Direct<sup>®</sup> program.<sup>7</sup>

*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

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<sup>7</sup> Catalina restricts the full purchase history to only 65 weeks, but we evaluate different lengths of purchase history.

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. 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  $P_1^f = \Pi_1^{10} - \Pi_1^{01}$ ;  $P_2^f = \Pi_2^{01} - \Pi_2^{10}$  and  $P_1^b = \Pi_1^{11} - \Pi_1^{01}$ ;  $P_2^b = \Pi_2^{11} - \Pi_2^{10}$ .

### ***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.<sup>8</sup>

*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 retailers take into account the coupons issued in setting retail prices.<sup>9</sup> 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  $i$  ( $i = 1, 2, \dots, H$ ) chooses one of  $J$  available brands (denoted by  $j = 1 \dots J$ ) 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  $t = 1, 2, \dots, n_i$ . 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  $j$  ( $j = 1 \dots J$ ) on shopping occasion  $t$  as follows:

$$u_{ijt} = X_{ijt}\beta - r_{jt}\alpha + I_{it}\gamma + \xi_{jt} + \varepsilon_{ijt} \quad (1)$$

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<sup>8</sup> Technically, manufacturers set the wholesale prices and Catalina decides whether to offer the coupon and what its face value will be, but this distinction is unimportant for the results after the manufacturer has made the decision to purchase the targeting service.

<sup>9</sup> For brevity, we only describe the Manufacturer Stackelberg model in the paper, though we also estimate the Vertical Nash model.

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  $t$ <sup>10</sup>,  $\xi_{jt}$  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.

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  $\varepsilon_{it} = (\varepsilon_{i0t}, \varepsilon_{i1t}, \dots, \varepsilon_{iJt})$  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)<sup>11</sup>. 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:

$$S_{ijt}^k = \frac{\exp(X_{ijt}\beta^k - r_{jt}\alpha^k + I_{it}\gamma^k + \xi_{jt})}{\sum_l \exp(X_{ilt}\beta^k - r_{jt}\alpha^k + I_{it}\gamma^k + \xi_{lt})} \quad (2)$$

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<sup>10</sup> 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.

<sup>11</sup> 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.

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:

$$S_{ijt} = \sum_{k=1}^K f^k S_{ijt}^k = \sum_{k=1}^K f^k \left( \frac{\exp(X_{ijt}\beta^k - r_{ijt}\alpha^k + I_{it}\gamma^k + \xi_{jt})}{\sum_l \exp(X_{ilt}\beta^k - r_{ilt}\alpha^k + I_{it}\gamma^k + \xi_{it})} \right) \quad (3)$$

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):

$$\Pr(i \in k | H^i) = \frac{L(H^i | k) f^k}{\sum_{k'} L(H^i | k') f^{k'}} \quad (4)$$

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  $H_{FH}^i$  plays an important role in our analysis, and we denote the corresponding posterior probability as:

$$\Pr(i \in k | H_{FH}^i) = \frac{L(H_{FH}^i | k) f^k}{\sum_{k'} L(H_{FH}^i | k') f^{k'}} \quad (4a)$$

### 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  $r_{1t}^{xy}, \dots, r_{Jt}^{xy}$ , conditional on which firms have purchased the 1:1 service to solve the following problem:

$$\max_{r_{1t}^{xy}, \dots, r_{Jt}^{xy}} \Pi_{Rt}^{xy} = \sum_{j=1}^J \sum_{i=1}^{N_i} [r_{jt}^{xy} - w_{jt}^{xy}] S_{ijt} (r_{jt}^{xy} - D_{ijt}^{xy}) M_t \quad (5)^{12}$$

where  $D_{ijt}^{xy}$  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 the total size of the market on occasion  $t$ . The shares  $S_{ijt} (r_{jt}^{xy} - D_{ijt}^{xy})$  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  $r_{jt}^{xy} - D_{ijt}^{xy}$ <sup>13</sup>. 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 the Web Appendix A. The retailer price equation can be derived as:

$$R = W - \left[ \sum_{i=1}^N \Theta_{iR} \right]^{-1} * \left[ \sum_{i=1}^N S_i \right] \quad (6)$$

Where  $\Theta_{iR}^i$  is the matrix of first derivatives of all the (individual consumers') shares with respect to all retail prices (retail prices are common across consumers), with element  $(j,m) = \frac{\partial S_{im}(r_m)}{\partial r_j}$ ,

$R$  is the vector of retail prices and  $W$  is the vector of wholesale prices (which are common across all consumers) and  $S^i$  is the vector of shares for each consumer 'i' over all the brands:

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<sup>12</sup> 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  $S_{ijt} (r_{jt}^{xy} - D_{ijt}^{xy})$ , which is a function of the effective price faced by the consumer of  $r_{jt}^{xy} - D_{ijt}^{xy}$  and (3)  $M_t$ , the total market size in time  $t$ .

<sup>13</sup> Note that we assume that the retailer uses the same level of information about consumers as that bought by the manufacturer from Catalina. Here, we follow the assumption made in the previous literature on targeting (e.g., Besanko, Dube and Gupta 2003) that both manufacturers and retailers use the same level of information. Relaxing this assumption to allow the retailer to use customer data, when manufacturer does not buy the CDI's service leads to a "common knowledge" problem because manufacturers do not know or cannot infer the demand model used by the retailer to set retail prices. Advances in game theory beyond the scope of this paper are needed to solve this problem.

$$R \equiv \begin{bmatrix} r_1 \\ \vdots \\ r_J \end{bmatrix}_{J \times 1}, \quad W \equiv \begin{bmatrix} w_1 \\ \vdots \\ w_J \end{bmatrix}_{J \times 1}, \quad S^i \equiv \begin{bmatrix} S_1^i \\ \vdots \\ S_J^i \end{bmatrix}_{J \times 1}$$

### Manufacturer

A manufacturer 'm' offering a subset  $\mathbb{N}_m$  of brands in the market sets the wholesale price  $w_{jt}^{xy}$  (where  $j \in \mathbb{N}_m$ ) 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 ( $r_{jt}^{xy}$ ) 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:

$$\Pi_{mt}^{xy} = \sum_{j \in \mathbb{N}_m} \sum_{i=1}^{N_i} [w_{jt}^{xy} - D_{ijt}^{xy} - c_{jt}] S_{ijt} (r_{jt}^{xy}(w_{jt}^{xy}, D_{ijt}^{xy}) - D_{ijt}^{xy}) M_t \quad (7)$$

where  $c_{jt}$  is the marginal cost of the manufacturer for brand  $j$  in period  $t$ , and  $S_{ijt}^{xy}(r_{jt}^{xy}(w_{jt}^{xy}, D_{ijt}^{xy}) - D_{ijt}^{xy})$  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.,  $D_{jt}^{xy} = \{D_{ijt}^{xy}\}_{i=1}^H$ .

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

$$\Pi_{mt}^{xyi} = \sum_{j \in \mathbb{N}_m} [w_{jt}^{xy} - D_{ijt}^{xy} - c_{jt}] S_{ijt} (r_{jt}^{xy}(w_{jt}^{xy}, D_{ijt}^{xy}) - D_{ijt}^{xy})$$

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  $w_{jt}^{xy} = \max_i w_{ijt}^{xy}$  and  $D_{ijt}^{xy} = w_{jt}^{xy} - w_{ijt}^{xy}$ .

From the manufacturer first order conditions, we can write the manufacturer margin from a particular household  $i$  [ $W_i - C$ ] as follows:

$$[W_i - C] = [O_w \bullet \Theta_w^i]^{-1} * [-S^i] \quad (8)$$

Where  $\Theta_W^i$  is defined 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  $(j,m) = \frac{\partial S_{im}(r_m - D_{im})}{\partial w_{ij}}$ . 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. where  $[O_W \bullet \Theta_W^i]$  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  $i$ :

$$W_i = \begin{bmatrix} w_1 - D_{i1} \\ \vdots \\ w_J - D_{iJ} \end{bmatrix}_{J \times 1}, \quad C = \begin{bmatrix} c_1 \\ \vdots \\ c_J \end{bmatrix}_{J \times 1}, \quad S_i = \begin{bmatrix} S_{i1} \\ \vdots \\ S_{iJ} \end{bmatrix}_{J \times 1}$$

The derivation is detailed in the Web 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 accessed 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  $H_{FH}^i$ ). 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.

$$c_{jt} = \lambda_j + \theta * B_t + v_{jt} \tag{9}$$

where  $B_t$  are the factor prices,  $\lambda_j$  are brand specific intercepts and  $v_{jt}$  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 customer data intermediary.

*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.<sup>14</sup> 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 Web Appendix B. Given the demand estimates, we can compute the wholesale and retail margins using the equations 6 and 8. Then the cost estimation reduces to a linear regression, where the dependent variable is (Retailer price – Computed Retail Margin – 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. Note that the demand model will no longer be as in equation 3. The demand equation will replace the segment probability  $f^k$  in equation 3 with the household level segment probability as obtained in equation 4 (or, for the full history case, in equation 4a). The share

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<sup>14</sup> 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).

equation used by a manufacturer to target a consumer ‘ $i$ ’ conditional on observed choice history  $H^i$  will thus be:

$$S_{ijt}^{H^i} = \sum_{k=1}^K \left\{ \left[ \frac{L(H^i | k) f^k}{\sum_{k'} L(H^i | k') f^{k'}} \right] * S_{ijt}^k \right\} = \sum_{k=1}^K \left\{ \left[ \frac{L(H^i | k) f^k}{\sum_{k'} L(H^i | k') f^{k'}} \right] * \left( \frac{\exp(X_{ijt} \beta^k - r_{ijt} \alpha^k + I_{it} \gamma^k + \xi_{jt})}{\sum_l \exp(X_{ilt} \beta^k - r_{ilt} \alpha^k + I_{it} \gamma^k + \xi_{lt})} \right) \right\} \quad (10)$$

*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 customer data intermediary.

## **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.<sup>15</sup> 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.<sup>16</sup> A first stage regression of ketchup prices with brand intercepts and factor costs (cost of tomatoes) was used. 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

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<sup>15</sup> 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.

<sup>16</sup> 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).

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 ( $p < 0.01$ ) is the Manufacturer-Stackelberg model with manufacturers in Bertrand Competition. 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 Customer Data Intermediary'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.<sup>17</sup> 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  $(\Pi_1^{10}, \Pi_1^{01}, \Pi_2^{10}, \Pi_2^{01}, \Pi_1^{11}, \Pi_2^{11})$  for different lengths of purchase history. Using these payoffs, we infer what price the customer data intermediary 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 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).

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<sup>17</sup> 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.

\*\*\* 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.<sup>18</sup> 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 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).

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<sup>18</sup> 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<sup>®</sup>). It should be noted that longer purchase histories can be better for 1:1 marketing provided consumer preferences do not change over time. Non-stationary consumer preferences could actually make longer purchase histories a liability, an extreme example of which could be consumer preferences in the fashion industry.

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<sup>19</sup>. 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.<sup>20</sup> In equilibrium, since Heinz targets almost entirely through coupons for the popular Heinz 32 oz, we profile only households receiving coupons for Heinz 32 oz. Heinz 32 oz targets the price sensitive households. Segment 3 (price sensitive,

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<sup>19</sup> This is consistent with the finding of Shaffer and Zhang (2002) that the benefits of price discrimination are greater for the larger market share firm

<sup>20</sup> 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’.

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 Customer Data Intermediary*

We next evaluate the optimal strategies for the customer data intermediary (CDI). Since the CDI 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 CDI can charge from selling to Heinz (denoted as firm 1) exclusively when selling the full purchase history is  $P_1^f = \Pi_1^{10} - \Pi_1^{01} = 74534 - 73260 = 1,274$ . 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 CDI 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 customer data intermediary 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 customer data intermediary 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 Customer Data Intermediation**

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 dis-intermediates the intermediary. 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 Customer Data Intermediary*

The retailer has two sources of increased profits as a customer data intermediary; 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<sup>21</sup> while profits from sales of 1:1 services increases by \$1,475.

\*\*\* Insert Table 10\*\*\*

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<sup>21</sup> In this respect our result varies from that in the theoretical analysis of Liu and Zhang (2006). Liu and Zhang (2006) find that retailer profits fall in the presence of personalized pricing. There could be several reasons for this: (1) They do not consider vertical differentiation in their model of consumer preferences (2) they do not model the store brand, which the retailer owns directly and (3) they assume consumer preferences are fixed, whereas empirically, we use a logit model where consumer preferences are stochastic. Shin and Sudhir (2006) show analytically that vertical heterogeneity in quantities purchased (similar to the heavy user/light user segment in this paper) and stochastic consumer preferences over time are required for firm profits to increase by using personalized pricing.

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 customer data intermediary network (such as the ‘Catalina Marketing Network’) but also because they can price their targeting services more aggressively than a ‘pure’ CDI such as Catalina.<sup>22</sup> However, there are two main disadvantages for retailers in entering the customer data intermediary 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 Client of a Customer Data Intermediary*

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

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<sup>22</sup> 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.

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.

## **6. Conclusion**

The potential for customer data intermediaries 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 customer data intermediaries.

Our analysis enabled us to obtain interesting substantive insights of interest to a customer data intermediary 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 customer data intermediary 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.<sup>23</sup> Indeed the retailer might be the most powerful potential competitor to Catalina in the future.

What would happen if there is competition among customer data intermediaries either because the retailer entered the market or if the retailer supplied the data to multiple CDIs? 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. It is quite possible that alternative channel structures may exist in other product categories / other retail chains, and it would be useful to study customer data intermediaries in product categories/retail chains where channel structures such as the Retailer Stackelberg or the Vertical Nash are more appropriate.

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.

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<sup>23</sup> 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.

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.

We have assumed in this paper that retailers use the same level of information as that purchased by the manufacturer from the customer data intermediary.<sup>24</sup> We make this assumption because of the need for “common knowledge” between the manufacturer and retailer in order to solve the manufacturer-retailer pricing game. The implications of relaxing this common knowledge assumption needs to be studied in future research, but this requires methodological advances in the game theory literature.

Finally, we hope that that the approach used in this paper will inspire additional research to facilitate decision making in other customer data intermediary 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

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<sup>24</sup> This is the same assumption as in Besanko, Dube and Gupta (2003). We thank an anonymous reviewer for raising this issue.

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.

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**Figure 1: Schematic of the Market**

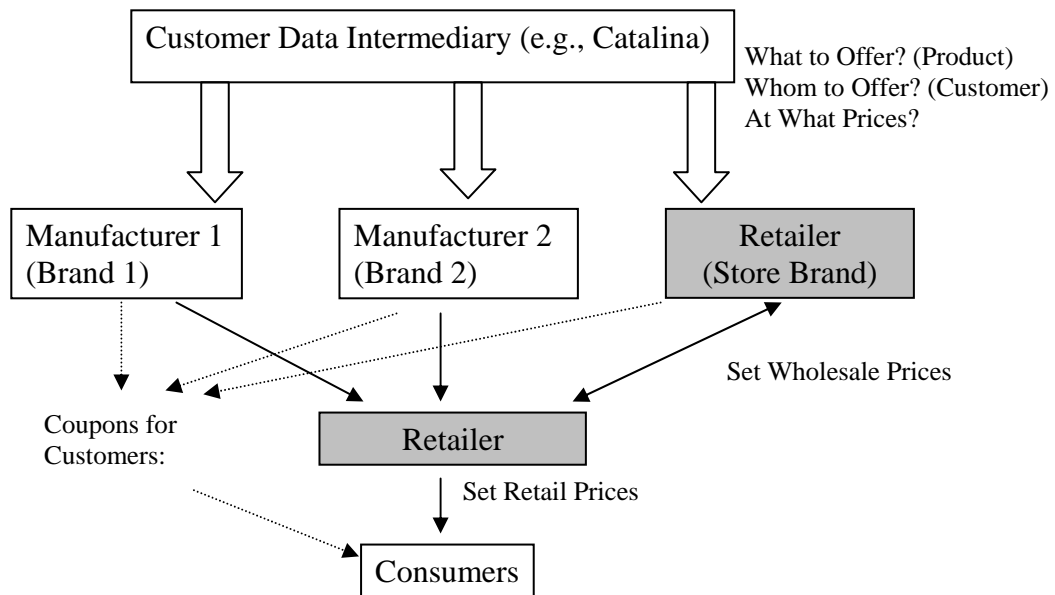


Figure 2: Decision Tree and Payoffs

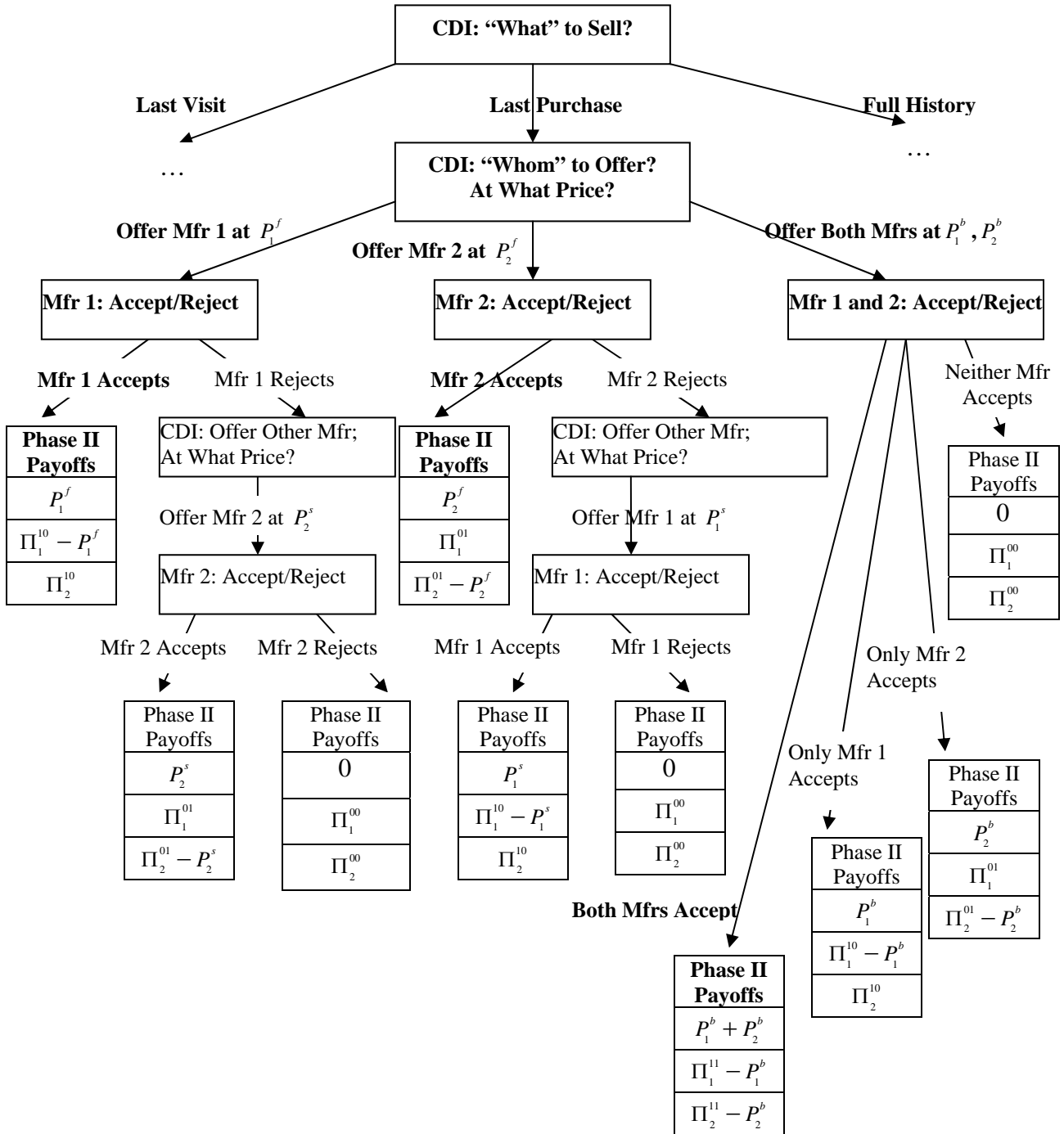


Figure 3a

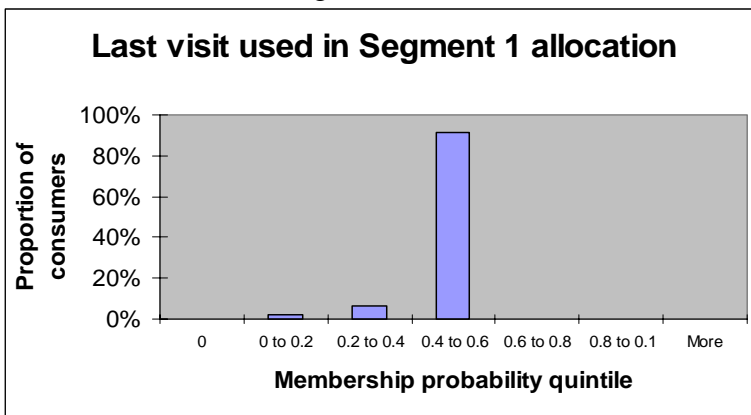


Figure 3b

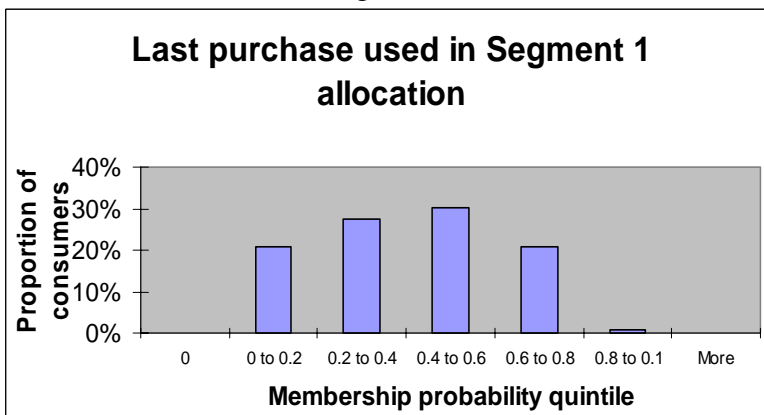


Figure 3c

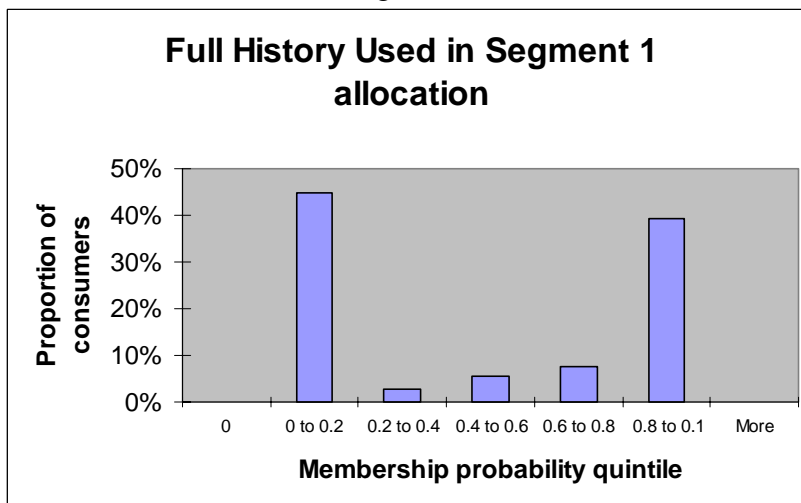


Figure 4a

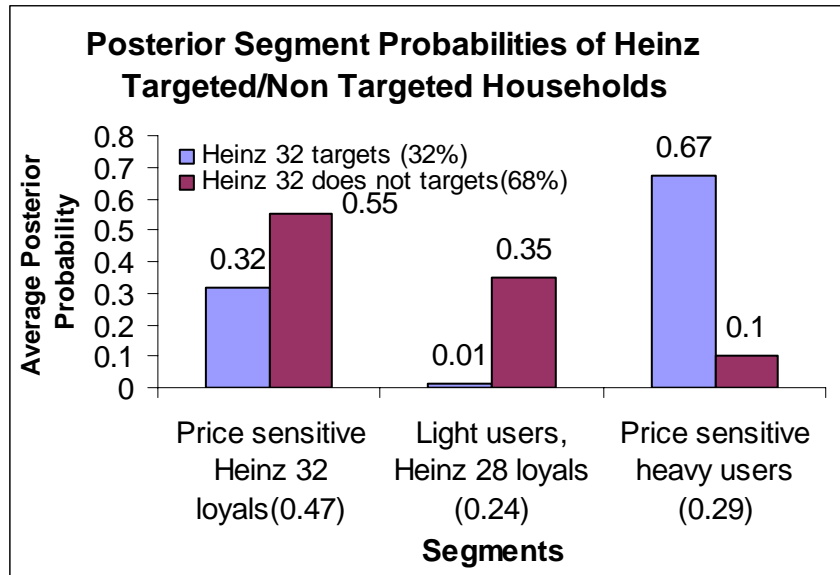
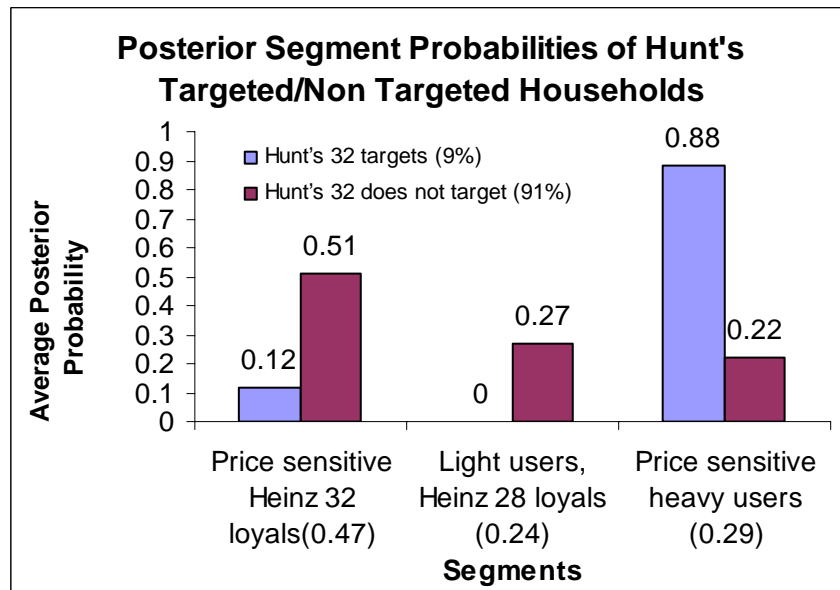


Figure 4b



**Table 1: Illustrative Set of Customer Data Intermediaries (latest available figures)**

Company/ Division	Revenue (\$ mil.)	% of total company revenue	Market Cap (\$ mil.)	Client profile, Client examples	Revenue Growth rate	Description
Catalina Marketing, Inc <sup>@</sup>	431	100%	1320	Manufacturers of packaged goods, grocery retailers e.g. Nestle, Safeway	8% p.a. over 2000-2004, non-core divestments reduced revenue in 2005	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.
DoubleClick, Inc (Abacus B2C division) <sup>#</sup>	105	35%	984	Catalog merchants, e.g., LL Bean, Sharper Image	10%(2004), 15.1% (2003)	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. Doubleclick was acquired by Hellman and Friedman LLC (a private company) in Q3 2005.
Experian's z-24 Division <sup>@</sup>	520	23%	NA	Catalog companies, e.g., Boston Proper, JJill, Retailers, non- profits	4% in 2005, 6% p.a. over 2001- 2004	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.
VT &NH's Direct Marketing Group's I-Behavior	NA	100%	NA	Catalog companies, e.g., Gardener's Supply, Vermont Country Store	NA	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.
Harte Hanks' Direct Marketing Division <sup>#</sup>	695	61%	2060	Retailers, finance sector, pharmaceuticals, telecom & high-tech	8.4% (2005), 9% (2004), 2% (2003)	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 <sup>@</sup> suite, inTouch), in-house data analytics, application and execution of campaigns.
Q Interactive (Owns Cool Savings, Inc) <sup>#</sup>	17.3 in Q3	NA	NA	Retailers, packaged goods manufacturers, e.g. Unilever, Land O' Lakes, Best Buy	20% p.a. over 2001-2004, 92% increase in Q3 2005 compared to Q3 2004	Cool Savings maintains a network of Web sites featuring online coupons, targeted marketing (from 20 million online consumers), lead generation, e-mail marketing, and loyalty programs for more than 1,000 companies in retail, packaged goods, and media industries. Cool Savings was taken over in Jan 2006 by privately owned Q Interactive, an online targeted marketing services provider for advertisers and publishers which uses demographic, behavioral and transactional data.

<sup>@</sup> 2005 figures

<sup>#</sup> 2004 figures

Table 2: Descriptive Statistics for Ketchup Data

	Conditional Brand share	Price (\$/ 10 oz)	Feature	Display
Heinz 32 oz	37%	0.41	0.07	0.11
Hunt's 32 oz	13%	0.42	0.02	0.01
Heinz 28 oz	22%	0.50	0.04	0.09
Store Brand 32 oz	28%	0.28	0.12	0.12

Table 3: Demand Model Estimates

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

\*\*\*p<0.01 , \*\*p<0.05,\* p< 0.1

Table 4: Mean Price Elasticities for the 3 Segment Model

<i>Change in Price</i>	<i>Change in Share</i>			
	Heinz 32	Hunt's 32	Heinz 28	SB 32
Heinz 32	-3.52	0.06	0.04	0.05
Hunt's 32	0.03	-5.18	0.02	0.09
Heinz 28	0.03	0.03	-2.20	0.03
Store Brand 32	0.03	0.11	0.02	-4.14

Table 5: Cost Equation Estimates

Parameter	Estimate (Std Err)
Heinz 32 oz	0.036 (0.072)
Hunt's 32 oz	0.088 (0.072)
Heinz 28 oz	0.038 (0.073)
SB 32 oz	-0.041 (0.072)
Tomatoes	0.152* (0.063)

\* p < 0.01

Table 6: Incremental Profits from 1:1 Coupons

Targeting by		Last Visit		Last Purchase				Full History			
		Heinz	Hunt's	Heinz	t-stat relative to Last Visit	Hunt's	t-stat relative to Last Visit	Heinz	t-stat relative to Last Purchase	Hunt's	t-stat relative to Last Purchase
Neither Hunts only	Profits	73,301	4,139	73,301		4,139		73,301		4,139	
	Profits	73,317	4,139	73,301	-7.80*	4,139	-0.99 <sup>ns</sup>	73,260	-2.92*	4,154	8.22*
	<i>% Increase relative to No Targeting</i> t-stat relative to No Targeting	0.02% 8.06*	0.00% -0.74 <sup>ns</sup>	0.00% 20.52*		0.00% -1.79 <sup>ns</sup>		-0.06% -2.84*		0.36% 8.13*	
Heinz only	Profits	73,304	4,139	73,620	38.41*	4,145	15.09*	74,534	27.64*	4,139	-7.27*
	<i>% Increase relative to No Targeting</i> t-stat relative to No Targeting	0.00% 3.43*	0.01% 8.82*	0.43% 37.36*		0.16% 16.19*		1.68% 35.84*		0.00% 1.39 <sup>ns</sup>	
	Profits	73,338	4,139	73,620	47.15*	4,145	13.53*	74,700	34.92*	4,174	13.02*
Heinz & Hunts	<i>% Increase relative to No Targeting</i> t-stat relative to No Targeting	0.05% 10.94*	0.01% 5.35*	0.44% 37.39*		0.15% 16.81*		1.91% 40.79*		0.84% 16.45*	

ns: not significant

\*:  $p < 0.01$

Table 7: Accuracy in Computing Targeting Profits

	Heinz profits (\$)	Hunt's profits (\$)
No firm targets (aggregate behavior)	66,628	4,116
No firm targets (true individual behavior)	73,301 (10.02%)	4,139 (0.56%)
Both firms target with last visit data	73,338 (10.07%)	4,139 (0.56%)
Both firms target with last purchase data	73,620 (10.49%)	4,145 (0.70%)
Both firms target with full history data	74,700 (12.12%)	4,174 (1.41%)

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

	<u>Both target using full history</u>	
	Heinz	Hunt's
Average increase in share	Hz 32: +0.3% Hz 28: +0.4%	Ht 32: +2.9%
Increase in (share weighted) margins	Hz 32: +2.8% Hz 28: +0.6%	Ht 32: +0.7%
Average increase in category purchase	+0.2%	

Table 9: Price and Customer Data Intermediary Profits under Alternative 1:1 Marketing Scenarios

	<u>Last Visit Based Targeting</u>			<u>Full History Based Targeting</u>		
	\$			\$		
	Price for Heinz	Price for Hunt's	Total Profits	Price for Heinz	Price for Hunt's	Total Profits
No firm targets	0	0	0	0	0	0
Hunt's only targets	0	0	0	0	15	15
Heinz only targets	0	0	0	1,274	0	1,274
Both firms target	21	0	21	1,440	35	1,475

Table 10: Incremental Retailer Profits from Customer Data Intermediation

	<u>Full History Based Targeting</u>		
	\$		
	Profits from Ketchup Profits	Profits from CDI	Total Retailer Profits
No firm targets	0	0	0
Hunt's only targets	1,040	15	1,055
Heinz only targets	0	1,274	1,274
Both firms target	1,133	1,475	2,608