The Effect of Modes of Acquisition and Retention Strategies on Customer Profitability

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Abstract

An important aspect of customer relationship marketing (CRM) is the need to acquire and retain profitable customers. Managers need to understand the relative effectiveness of different modes of acquisition, and loyalty programs. Very few studies have focused on the profitability of customers based on the methods used to acquire them and retain them. We answer these questions using a proprietary data set from the credit card industry. Prior studies have tested for differences in profit between modes of acquisition and retention by treating these variables as exogenous. Since customers choose the mode of acquisition and retention, this omission could lead to bias in the estimates. We develop a model to incorporate the endogeneity of modes of acquisition and retention and highlight the reduction in bias. We find that internet and direct mail generate more profitable customers than telemarketing and direct selling. We then examine the role of two popular customer retention strategies, namely, reward cards and affinity cards in driving customer profitability. Surprisingly, we find that customers with reward cards and/or affinity cards are less profitable than those customers without access to these retention strategies. We provide possible explanations for these findings. Our work adds to the growing literature in CRM and our results have important managerial implications for resource allocation among acquisition and retention strategies.

1. Introduction

The growing interest in customer relationship management (CRM) practices has spawned a number of research studies that investigate the effect of customer acquisition and retention strategies on a firm's performance. The importance and relevance of analyzing the customer-firm relationship is widely accepted by practitioners. Academic research has investigated how relationship marketing affects performance in business-to-business (B-to-B) and in business-to-consumer (B-to-C) markets (for a review of the literature see Berger et al. 2002)

The key to a firm's success in customer relationship management lies in identifying, targeting, attracting, and retaining profitable customers. While some papers have studied the efficacy of retention strategies (e.g., loyalty programs) on stated repurchase intention and repurchase behaviors (Bolton, Kannan, and Bramlett 2000), there is limited research on the effect of retention strategies such as reward and affinity programs on profitability. Reward programs give points for transactions which can be redeemed for rewards (e.g. frequent flier program) while affinity programs reward a particular group that the customer strongly identifies with. The published studies have also focused on grocery loyalty programs. Our study fills a gap in the literature by examining the role of reward and affinity programs on profit in the credit card market, a large trillion dollar industry. To our knowledge, this is the first paper to study the impact of affinity programs on profit.

Similarly the effect of different acquisition channels (direct mail, telephone solicitation, etc.) in generating profitable customers is under researched. Some recent papers have studied the relationship between modes of acquisition (or contact channels) and profitability and retention rates. Reinartz, Thomas, and Kumar (2005) study the effect of the number of contacts made through different modes (e.g., telephone, face to face, web, email) on profitability in a B2B context. They find that a more involving and interpersonal contact channel such as face to face and telephone are related to profitable customers and are associated with a higher probability of acquisition and a longer customer lifetime. Venkatesan and Kumar (2004) also study the role of modes of contact (face-to-face meetings versus direct mail, telephone, web) on purchase frequency and contribution margin in a B2B context. Our work is different from the above studies in two ways. First, we focus on a B2C context, in which the relationship between modes of acquisition and profit could be different from that observed in B2B situations. B2C customers do not have as strong an incentive to develop a long term relationship with the firm as B2B customers. Moreover, given current practices in which new customers are selectively given preferential discounts, there may be a strong disincentive to stay with a single firm. Second, the above papers consider modes of ongoing contacts with customers and the consequent effect on performance indicators, while we are interested in differences between customers who have been acquired through one of four modes.

Verhoef and Donkers (2005) study impact of acquisition channels on probability of retention and probability of cross buying in the context of an insurance services provider. They study four channels - mass media, direct marketing, Internet, and word of mouth. They find that direct mail acquisition performs poorly on retention and cross selling while radio and TV perform poorly for retention. Those customers acquired through the company's website have a higher retention rate. Though our objective is similar to theirs, we focus on the relationship between modes of acquisition and profitability. Further, their probit model does not consider selection bias, which arises due to the fact that customers choose a channel that is attractive. We contribute to the methodology by showing that it is not enough to merely assess the differences in performance between different modes of acquisition, ignoring the potential bias due to customer self-selection. Thus, in our model we properly control for selection bias and empirically test the relationship between modes of acquisition and profit in a different B2C context. We show that the selection bias is significant and affects the results in a major way.

We use data on credit card transactions from one bank to understand the role of loyalty programs (specifically reward cards and affinity cards), and modes of acquisition in generating profitable customers. We wish to empirically investigate whether some acquisition modes result in more profitable customers than other modes. Since there may be synergistic effects (or otherwise) between acquisition modes and loyalty programs, we also examine the interaction effects between them. There has been call to examine such interaction effects (Bolton, Lemon and Verhoef 2004) but has not been studied extensively. An exception is Reinartz, Thomas, and Kumar (2005), which finds significant positive interaction between face-to-face contacts and email and between telephone and email in a B2B context.

We selected the credit cards market due to its size and importance to the U.S. economy. In the past fifty years, this industry has grown from a million dollar business to over two trillion dollars in loans in 2003 (CardTrak 2/13/04). Further consumer use of revolving credit increased 9.2% during 2002-2003. The typical U.S. household carries eight credit cards with a revolving balance exceeding $7,500 (McGeehan 2004). U.S. card issuers made $2.5 billion a month in profit before taxes in 2003 (McGeehan 2004) and net income on credit card loans was 18.4% in 2000 (Lee 2001). Thus, the importance of the financial services industry to the U.S. economy is undeniable. Moreover, credit card firms generate rich databases containing elaborate customer transaction histories and demographics.

In summary, the contributions of our study are as follows. We believe that this is the first paper to study the link between affinity card programs and customer profitability. While prior studies have examined the reward card programs in grocery stores or airlines, this is the first to examine the link between such programs and profits in a different context. We develop a theory for the effects of different modes of acquisition on profit using customer effort and ease of targetability as the primary drivers. Further, we develop a model that properly accounts for selection bias of the different modes of acquisition and retention programs and estimate the model using hierarchical Bayesian techniques. If there are unobserved factors that affect a consumer's choice of the acquisition channel or of the retention program and these factors are correlated with the customer's transaction behavior, then there is potential for bias by ignoring self-selection. We show that such bias is non-trivial and cannot be ignored. Finally while some similar studies have been conducted in a B2B context, this paper studies an important industry in a B2C context.

We find a surprising result that, contrary to popular belief, both reward card and affinity card customers generate less profit than customers who do not have such cards. We provide a possible explanation for these findings. Further, we find that Internet and direct mail channels for customer acquisition generate more profitable customers than other channels such as telemarketing and direct selling. We tested for and found very little evidence of interaction effects between the modes of acquisition and the retention programs. These findings have important managerial implications for the financial services industry. We believe that managers can use these models and results to improve their targeting of profitable customers.

The rest of the paper is organized as follows. In section 2 we provide the relevant background for our study and a brief overview of research in the financial services industry and relationship marketing areas. In section 3 we discuss the characteristics of our unique dataset. Next, we discuss the models to be estimated. We present our results in section 5. Finally we conclude with a discussion of possible explanations for our results which run counter to managerial expectation and established research.

2. Literature review

2.1 Relevant literature in relationship marketing

A number of papers in customer relationship marketing have studied the efficacy of acquisition strategies and retention strategies in affecting customer lifetime and lifetime value (Reinartz, Thomas and Kumar 2005, Venkatesan and Kumar 2004, and Verhoef and Donkers 2005). The first two papers use data from a business-to-business context and find that interpersonal channels of communication such as face-to-face and telephone are associated with greater lifetime and profitability of customers. Note that these papers study the effect of ongoing communications by the firm through these channels, while we study the effect of the channel through which the customer was acquired. Moreover, these results may not be generalizable to a B2C context because of the reasons stated earlier. Therefore it is important to study the effects of acquisition mode on profits in a B2C context. Our study is similar to Verhoef and Donkers (2005) with respect to understanding the effects of modes of acquisition. Unlike their study which focuses on retention probability and cross selling, we focus on customer profits. Further, we extend their model by controlling for and showing the importance of accounting for self-selection by customers.

Reicheld and Sasser (1990) highlighted the importance of retaining customers and showed that firms could increase their profits by 25 to 85 percent by reducing their customer attrition by only 5 percent. The reasons for an increase in profits from existing customers can be attributed to lower cost of retaining them, their tendency to purchase more and try more products while requiring less servicing (Fornell and Wernerfelt 1987, 1988, Reichheld and Sasser 1990, Reichheld 1993, Sheth and Sisodia 1995). These arguments have been challenged in Dowling and Uncles (1997) who claim that for low involvement purchases, the above arguments may not hold.

The empirical evidence related to the effects of loyalty programs is mixed. Reinartz and Kumar (2003), show a positive association between loyalty programs and profitable lifetime duration for a catalog retailer, while Lewis (2004) finds that loyalty program motivated customers to increase their purchase levels in an online grocery retail setting. Rust, Lemon and Ziethaml (2004) found that investment in loyalty program significantly increased the CLV in the context of airline data. Other researchers found no effect of loyalty programs on share of wallet (Sharp and Sharp 1997). Bolton, Kannan and Bramlett (2000) hypothesize a positive association between membership in credit card loyalty programs and performance measures such as retention, service usage, and customer share. Their empirical results do not find strong evidence of main effects but find evidence of interaction effects leading them to conclude that loyalty programs help a customer discount negative evaluations of the company relative to its competitors. They do underscore the need for research that links loyalty programs to purchases and profits. Even if reward programs increased lifetime or retention, it is not clear that long lived customers will be profitable as shown in Reinartz and Kumar (2000). The above research focuses on loyalty programs that offer *points for purchase* (much like the reward card program in our data) but do not consider the role of affinity based programs.

Research of affinity cards is much more limited. Machiette and Roy (1992) describe affinity marketing and distinguish between nominal affinity and true affinity based on the affinity strength (based on level of participation and duration) and social disclosure (pride in overtly revealing group membership). Swaminathan and Reddy (2000) suggest that non-profit organizations are better candidates for affinity marketing than commercial firms as the affinity is the former case is based on the individual's characteristics rather than the product or service characteristics in the latter. Woo, Fock and Hui (2006) present experimental evidence to show that attitude towards the affinity group (the beneficiary) affects the attitude and beliefs towards the affinity card. Thus we see that while prior research has focused on behavioral effects of affinity programs, there is no research on the transaction, or profit implications of affinity card programs.

2.2 Institutional details of the credit card industry

Customer profit in the credit card industry is obtained from three primary income streams - interest income on borrowed money, interchange fee from transaction income, and fees. The largest component of profit is from interest income from *revolvers* (those customers who do not pay the monthly balance in full) and *borrowers*. Approximately 78% of the total account revenue is derived from interest on outstanding balances (Min & Kim 2003). Interchange fee is the percentage charged to retailers (ranges from 1.5-2%) on transaction amounts. Fees comprise of annual fees and fees charged for negative customer behavior such as over-the-limit fees, late payment fees, and returned check fees. Americans paid an estimated $30 billion in financial services fees in 2004; an increase of 18% over 2003 (CardTrak 1/13/05).

From a customer's point of view, credit cards provide two primary benefits - as a medium of convenient exchange and as a source of short-term or intermediate term revolving credit (Garcia 1980). The revolvers are generally more profitable than convenience seekers (Kumar and Reinartz (2006, p72). Credit cards customers are acquired through one of four modes of acquisition – direct mail, telephone, Internet, and direct selling. The first three modes are self explanatory. Unlike in a B2B context, direct selling here refers to setting up of booths at events (sports, fairs etc.) and other locations (e.g., universities) and getting customers to apply for a credit card. Usually, there is a small gift that is used as an inducement. The two most popular retention strategies in credit card markets are the use of affinity cards and reward cards. Reward cards offer points for every dollar spent and these points can be redeemed for rewards. Most of the reward cards have an annual fee. Affinity cards tend to tap into the affinity that the customer has for his university, church or other group by offering a co-branded card and paying a certain percentage of a customer's transaction amount to the group.

2.3 Hypotheses development

We develop a framework that allows us to think of how particular modes of acquisition affect customer profitability. We recognize two factors. On the consumer side, we are concerned with the effort required to apply for a card. On the firm side we are concerned with the ability to effectively target prospective customers. This novel framework allows us to generate testable hypotheses.

We view acquisition as resulting from consumers' decision to apply for a card, followed by the card issuer's decision to issue the card. A consumer can be thought of as maximizing utility, weighing the benefits from the card and the cost of getting it. At the time an application is made an important element of the cost is the effort required to make the application. We therefore posit that for acquired customers, ex-ante, the benefit of the card exceeds the cost of applying for the card. Of-course this cost varies with mode of acquisition. A customer acquired through a method that imposes higher cost of effort should also be expected to have higher benefits from the card. Benefits are derived from use of the card. So, customers who have put in greater effort to acquire a card are also likely to be the ones that use the card more for purchases and credit. In other words, we can expect that if a customer is acquired through a mode which is costly to him (her), such a customer would use the card more. This argument suggests that the mix of customers in terms of card usage would differ systematically across modes of acquisition. In our application, direct mail (DM) requires the customer to complete the application and mail it. There is little or no input from the firm at this stage. Likewise, acquisitions from the internet (INT) require the customer to search and go to the site and fill out the application. We can contrast this with two other modes of acquisition. Telesales (TS) typically walks a customer through the application process. Direct sales (DS) also requires comparatively less effort from the customer. This argument is consistent with the findings of Cardozo (1965) and Clarke and Belk (1979) who show that higher level of customer effort leads to a higher rating of the product and greater customer satisfaction. One finds support for this argument in the data. We look at the average number of days it took a customer acquired through different modes of acquisition to use the card for retail purchase or to take out cash after receiving the card as a measure of the latent need for a credit card.

	Average # of days to retail	Average # of days to cash
Internet (INT)	189	813
Direct Mail (DM)	265	587
Direct sell (DS)	507	919
Telesales (TS)	686	894

From the above table we see that the average number of days to first retail transaction is lower for Internet customers and direct mail customers. Telesales customers appear to be least interested in using the credit card. Direct mail customers also are faster to take out a cash loan.

The mix of customers could also be affected by the firm's ability to target customers. For example, if the firm can identify customers who are more profitable they could target them selectively. Again, the ability to effectively target customers varies across the different modes of acquisition. Clearly targeting requires data on customers. With the availability of lists such data is increasingly available. In our application we do not know to what extent the firm actually implemented targeting. However, in the case of TS and DM, the cost of contact is mainly a variable cost and so it is reasonable to assume that some level of targeting would be pursued. In contrast, INT was used by the firm to allow customers to visit the company website and make an application from there. There was no attempt to screen customers. Of-course given that most of the cost of developing the web application is a fixed cost, it makes sense to not screen at this stage.[1] Finally, the firm employed DS by having booths in public places such as shopping centers, college campuses and public events. No attempt was made to screen prospective applicants in this mode of acquisition. Again, given the large fixed cost of setting up booths this makes sense.

Taken together, the targeting ease and customer cost of applying both determine the mix of acquired customers in terms of card use (benefit) as well as profitability. Of-course, customers that don't use the card are not profitable. Card users are more, or less profitable depending on how they use it, whether for purchases only or for obtaining credit. The four modes of acquisition can now be classified in terms of targeting ease and customer cost of applying as shown in Figure 1.

[1] It may still be optimal for the firm to screen customers before processing to save on variable costs of processing.

Figure 1: Relationship between Modes of acquisition, Ease of Targetability, and Effort

	Greater ease of Targetability	**Lesser ease of Targetability**
High Effort	Direct Mail (DM)	Internet (INT)
Low Effort	Telesales (TS)	Direct selling (DS)

The two modes TS and DM are similar in that they allow the firm to target. The difference between them is that DM requires higher effort from the customer. This in turn means that customers acquired through DM are likely to be heavier users of card benefits, and therefore likely to be more profitable. We therefore hypothesize that DM customers are more profitable than TS customers. We will denote it as DM>TS. Turning to DS and INT, these are similar in that the firm made no attempt to target based on profitability. Since INT requires higher effort from the customer, as before we argue that INT>DS. Next we can compare TS and DS. Both these methods require little consumer effort. However, targeting is likely with TS. We therefore hypothesize that TS>DS. Finally, both DM and INT require high consumer effort. Since INT made no effort to target, while DM allows targeting, we hypothesize that DM>INT. Combining these inequalities, we have

$$DM > INT, TS > DS$$

Note that we are unable to establish a clear inequality between INT and TS. Obviously, it would depend on whether targeting is more salient than consumer effort in this particular application. We state our hypotheses as follows:

H1a: With respect to customer profit, we expect that direct mail is better than Internet

H1b: With respect to customer profit, we expect that direct mail is better than telesales

H1c: With respect to customer profit, we expect that direct mail is better than direct sales

H1d: With respect to customer profit, we expect that Internet is better than direct sales

H1e: With respect to customer profit, we expect that Telesales is better than direct sales

Affinity cards and profit

Affinity card programs are designed to capitalize on the loyalty the cardholder feels towards the endorsing organization while providing a competitive advantage to the issuing bank by allowing them to protect their margin (Schlegelmich and Woodruffe 1995). Research has shown that many consumers carry the endorsed card in the "front of purse/wallet" (Worthington, 2001a). After an account is opened, the affinity card encourages usage and reduces customer attrition (Worthington and Horne 1998). They also find that solicitations based on affinity have a higher response rate than other solicitations. Most of the research is descriptive and relies on surveys of consumers, bank managers and endorsing organizations. There is no empirical study in the literature on the profitability or otherwise of affinity cards.

Academic research on affinity programs has considered the behavioral aspects of the affinity card. Machiette and Roy (1992) provide a taxonomy of affinity groups and propose distinguishing between true affinity and nominal affinity (as in the case of frequent flier miles programs). True affinity is defined by two factors - affinity strength and social disclosure. Affinity strength depends on the level of participation and social interaction with the group as well as the length of time as a member. Social disclosure is the willingness of a person to reveal the membership in a group to the general public. Based on the classification, they conclude that affinity programs involving a non-profit group is better than that with a for profit group. They also suggest that paid membership in a group is positively correlated with affinity strength. Woo, Fock and Hui (2006) show that attitude towards an affinity group positively affects a customer's behavioral intention to use and the affinity card beliefs but not the attitude towards the affinity card. Thus we see that the research on affinity cards is sparse and our paper seeks to study the profitability of an affinity card customer relative to non-affinity card customers.

If, as the research above suggests, affinity card affects customer usage and duration positively, we may expect that affinity card holders will have higher transaction amounts than non affinity cardholders. Further, if customers stay longer with the bank, then we should expect increased customer profitability (Reicheld and Sasser 1990). However, customers that obtain affinity credit cards do so because they have a perceived psychological benefit from the association with a group such as a church or a university. Thus their primary motivation for obtaining a card is neither convenience nor credit, and so while these customers may use the card more and shift transactions from competing cards, they may not be motivated to revolve balances, which is the main source of profit for the bank. Further, most arrangements between the credit card company and the endorsing organization are such that the latter gets a percentage of the transaction amount, not revolved balances. Such information may encourage a customer's use of the card, but it need not induce revolving behavior. Finally, unless any increase in profit due to affinity card offsets the additional cost of the affinity program, it may not yield higher net profits. Based on these arguments, we propose the following two hypotheses.

H2a: Customers who own affinity cards will have higher transaction amounts than non-affinity card customers.

H2b: Customers who own affinity cards will have lower finance charges and hence lower profit than non-affinity card customers.

Reward cards and profit

In contrast to the affinity program, reward programs benefit the consumer directly with either free goods or airline travel based on points earned per dollar of purchase. It is conceivable that cardholders would prefer programs that benefited them directly rather than benefiting an endorsing organization (Nichols 1990). The goal of reward programs is to drive usage and ultimately profitability through repeat purchase behavior (Dowling and Uncles 1997; Heskett, Sasser and Schlesinger 1997). Therefore, we should expect reward card holders to have a higher average transaction amount relative to non-reward card holders, if the program drives usage.

Previous research has shown the reward programs (in airline frequent flier program) can increase switching costs for the customer (e.g. Kopalle and Neslin 2003, O'Brien and Jones 1995). Customers are required to invest varying degrees of effort to attain rewards (Kivetz and Simonson 2002). Perceived effort is defined as any inconvenience (such as buying with a particular credit card or buying at a particular store) that is necessary to comply with the reward program requirements. If a customer has invested a significant amount of effort into the reward program (e.g., obtained 20,000 of the required 25,000 miles required to earn a free ticket), s/he is less likely to switch to a competing airline for their next trip. Thus by increasing switching costs, firms can increase their retention rate (Perrien, Filiatrault, and Ricard 1992). This suggests that reward programs would increase the duration of a customer's relationship with the credit card company and thus could increase the interchange fee through higher transaction amounts. In contrast, Hartmann and Viard (2008) use a dynamic structural model of reward program for golfers and find that the switching cost effect applies only to infrequent golfers (who comprise a small segment about 20%) but not to frequent golfers. They conclude that the switching cost is not high due to a reward program.

The evidence regarding the effectiveness of reward programs in a retailing environment is mixed. Dowling and Uncles (1997) conclude that store loyalty card programs are “surprisingly ineffective”. Sharp and Sharp (1997) found no evidence to support an increased penetration or purchase frequency resulting from reward programs. Similarly there appears to be little effect on individual customer loyalty as indicated by share of wallet (East, Hogg and Lomax 1998). In contrast Dreze and Hoch (1998) report an increase in category sales, transaction size (quantity), and store traffic due to a frequent shopper program offered for a baby products category.

To reconcile the above contradictory findings, research studies examine the conditions under which reward programs are beneficial to the firm. Lal and Bell (2003) find that such programs are profitable because of incremental sales to casual shoppers and not due to loyal shoppers. Kim, Shi, and Srinivasan (2001) use an analytical model to study why the type of reward program and the amount of reward varies across programs. They conclude that firms gain from reward programs as long as light users are not very price sensitive.

In the economics literature, Klemperer (1987) suggests another benefit of frequent shopper reward programs which is reduced price competition through the creation of switching costs. Note that reduced price competition increases firm profits, but may not affect customer profitability. Similarly, Kim, Shi, and Srinivasan (2001) also find that the major consequence of reward programs is to raise the price of the product in the market. Depending on the elasticity of demand with respect to price the profits would either increase or decrease for the firm when the price increases. In our context, if the average APR increases due to reduced price competition effect of reward cards, it is not clear whether the profits would rise or decline.

An interesting aspect of the reward program in credit card marketing is that rewards are given for behavior that is not the primary profit driver for the firm. As stated earlier, much of the customer profitability from credit accounts is driven by interest income. However, the customer earns reward points for charging transactions to their card rather than for carrying interest-generating balances. Thus this program may attract a larger proportion of "convenience users" (those who pay their balances in full each month) relative to customers who use the credit card for loans. There is support for this assertion in our data. Over a 36 month period, 39% of non-reward card customers had "balance subject to finance charges" equal to zero, which means that these customers paid on time and incurred no finance charges. For reward cards holders, the corresponding percentage was 45%. The adverse effect of the reward card program on the proportion of 'convenience users' vis-à-vis 'balance revolvers' will have a negative effect on overall profitability. Therefore, we expect that the profitability of the reward card customer is likely to be less than that of the non-reward card customer.

H3a: Customers with reward cards will have higher transaction amounts than those without reward cards.

H3b: Customers with reward cards will be less profitable than those without reward cards.

3. Data Description

Our dataset covers a three-year time period representing approximately 9000 accounts all starting their relationship with a financial services provider at the same time. Customers in the sample range from highly active customers who transact many times per month to inactive customers who fail to activate their account during the length of the study. The variables of interest in the data set provide information on customer transaction amounts and finance charges, how they were acquired, whether they had an affinity card or not, and whether they had a rewards card or not. For the profit calculation, the transaction history provides information on the date of the transaction, the type of the transaction (retail or cash advance), and the amount of the transaction. The other variables in the data include area of primary residence, occupation, number of cards issued on the account (CARD_COUNT), credit line (LINE), and type of card (PREMIUM, PLATINUM, GOLD, or STANDARD).

In table 2, we report the descriptive statistics. After deleting households that had missing information in some of the fields, we had 8802 usable observations. The average profit per customer is $847, and average finance charges are $832.61. This supports the idea that the bulk of the profits in this industry are derived from finance charges. About 20% of the customers own a reward card and 83% of customers own affinity cards. A large percentage of customers were acquired by direct mail (42%) and telesales (40%) while direct selling and internet account for the rest. The sample is a stratified random sample from the total set of customers who obtained their account in the same month. The strata used were the different types of affinity cards to allow for better investigation of the profitability of affinity cards. In table 2b we report the coefficient of variation for profit, total transaction amounts and for finance charges. We see that CV for all measures of profit is high for direct selling and telesales relative to the other two channels. Thus these channels attract a pool of more heterogeneous customers.

In the current dataset, customers are acquired from one of four sources: direct mail, Internet, telemarketing or direct selling. Direct mail accounts are those that result from the customer receiving a direct marketing solicitation and financial services application in the mail, and responding to the offer. Telemarketing accounts result from outbound telephone calls made to the customer. Direct selling accounts result from face to face interaction between the customer and the firm at venues such as professional sporting events, alumni association gatherings, and professional conferences. Internet accounts are primarily the result of banner advertisements that result in a click-through and subsequent application. We are interested in quantifying the profit implications of these four modes of acquisition.

We used a number of covariates to control for observed heterogeneity. There is evidence in the literature that social class (Mathews and Slocum, 1969) and age (Mathur and Moschis, 1994) affect credit card use. We use occupation dummy variables as a surrogate measure for the effect of social class. We also use type of credit card (gold, platinum etc) as an indicator of customer attractiveness as determined by the bank. We use card_count (number of cards from this bank) as a measure of household commitment to the card. Finally we use geographic dummy variables to control for variations in spending patterns in different regions of the country.

Customer Profitability

Customer profitability can be simply defined as the net dollar contribution made by individual customers to a firm (Mulhern 1999) and has been conceptualized in academic literature in several ways such as lifetime value (Keane and Wang 1995), customer valuation (Wyner 1996), customer lifetime valuation (Dwyer 1997), customer relationship value (Wayland and Cole 1997), customer equity (Blattberg and Deighton 1996, Rust, Zeithaml, and Lemon 2000, Blattberg, Getz and Thomas 2001), and customer lifetime value (Berger and Nasr 1998, Reinartz and Kumar 2000, 2003, Reichheld and Sasser 1990).

By viewing customer as an asset and evaluating expenditures on customers in terms of expected returns, customer profitability becomes a central tenet of customer relationship marketing (Morgan and Hunt 1994). With an understanding of individual level customer profitability, managers have the ability to develop targeted communication programs based on actual or expected profitability. Firms can also use profit metrics to target customized retention efforts at segments based on profitability (Mulhern 1999).

Customer profitability can be calculated based on present purchase behavior or anticipated future stream of purchases (Mulhern 1999). Sophisticated databases containing detailed purchase histories over multiple years provide the critical input for developing these measures of customer profitability. We do not employ customer lifetime value (LTV) as a dependent variable in our investigation, since one needs an accurate estimate of customer lifetime to compute LTV. Instead, we use a measure of customer profit computed directly from the transaction amounts and costs associated with each customer. We believe that the substantial results will not change if we use LTV.

Customer profitability for financial services customers can be readily calculated using a historical profitability model that considers aggregate purchase amounts, unit costs, and variable marketing expenses for each period with an adjustment for the time value of money. An example of a historical profitability model is provided by Mulhern (1999):

$$CP_i = \left[\sum_{t=1}^{T} \left(\sum_{j=1}^{J_i} (p_{ijt} - c_{ijt}) \right) - \sum_{k=1}^{K_u} mc_{ikt} \right] (1+I)^t$$

where CP_i = profitability of customer *i* to a firm, p_{ijt}= the price of purchase *j* made by customer *i* in period *t*, c_{ijt}=unit cost of purchase *j* made by customer *i* in period *t*, mc_{ikt}=variable marketing cost *k* for customer *i* in period *t* and I=discount factor for the time value of money.

We use a historical profitability model that translates for financial services as follows. It includes the three sources of income – finance charges (FCI), interchange income (a percentage of transaction amount), and fees, and two account level variable costs for the reward program, and affinity group compensation.

$$\mathrm{PROFIT}_i = \left[\sum_{t=1}^{36}\left(\mathrm{FCI}_{it} + \mathrm{INT}_{it} + \mathrm{FEE}_{it} - \mathrm{RC}_{it} - \mathrm{GC}_{it}\right)\right]\left(\frac{1}{1+r}\right)^t \qquad (1)$$

where PROFIT_i= profitability of customer *i* to a firm,

FCI_{it}= the monthly finance charges paid by customer *i* in period *t*,

INT_{it}= monthly interchange generated by customer *i* in period *t* (this is a fixed percentage of transaction amount),

FEE_{it}= monthly fees paid by customer *i* in period *t*,

RC_{it}= Reward program loyalty expense cost for customer *i* in period *t*,

GC_{it}= Affinity group compensation cost for customer *i* in period *t*,

r = monthly discount rate (based on 15% per year)

In the above equation, we use average interchange income, reward card costs and affinity card costs using industry average percentages of transaction amounts. For customers who never used their card, PROFIT is set to be zero. Note that we have not deducted the cost of acquisition or the costs of retention efforts which could vary over customers. This is a limitation of data unavailability and does not affect the model or the main results.

4. Model

In order to study the relationship between customer profitability, modes of acquisition, affinity marketing and rewards program we employ a simple left-censored Tobit model with customer profit (PROFIT) as the dependent variable. The dependent variable is censored because PROFIT is observed only if a customer uses the credit card. It should be noted that there are a few customers with negative profits (about 200 out of 9000). Since all customers started at the same time (i.e., the first month in the data) and we did not deduct the fixed acquisition cost, there is no reason for the profit to be negative. We treated negative values as zero profit. The Tobit type 1 model is of the form:

$$y_i^* = X_i\beta + \varepsilon_i$$
$$with \qquad \varepsilon_i \sim N(0,\sigma^2)$$

where the latent random variable y_i^* linearly depends on X_i, a vector of explanatory variables, and the error term ε_i is independently and normally distributed with mean 0 and variance σ^2. The observed value of the dependent variable is censored below 0. Therefore,

$$y_i = \begin{cases} y_i^* & if \quad y_i^* > 0 \\ 0 & if \quad y_i^* \le 0 \end{cases}$$

OLS regression would yield biased estimates of β as $E(y_i|x_i)$ is not a linear function of x_i.

In order to better understand the drivers of the different sources of profitability, we develop our main econometric model. Profit for a credit card bank comes essentially from two sources – interchange fees and finance charges. Interchange fees are charged to the firms that accept the credit card transaction and are a fixed percentage of transaction amounts (TOTTRANS). We only know the average interchange fee rate charged to the firms (=1.6% of transaction amount), even though different firms could be paying different but fixed rates. Therefore, we use TOTTRANS as one of the dependent variables to represent the income from interchange fess. The finance charges (TOTFC) are calculated by the bank based on the balances carried by the customer beyond the grace period and the assigned APR rates for different types of balances (i.e., whether cash balance or retail balance). The dependent variables TOTTRANS and TOTFC may be correlated due to the fact that the sum of transaction amounts and balances carried should be less than the credit line. We therefore estimate a bivariate TOBIT model with two dependent variables y_{1i}^* (TOTTRANS) and y_{2i}^* (TOTFC).

$$\begin{pmatrix} y_{1i}^* \\ y_{2i}^* \end{pmatrix} \sim N_2\left(\begin{matrix} y_{1i}^* \\ y_{2i}^* \end{matrix}\middle| \begin{matrix} X_{1i}\beta_1 \\ X_{2i}\beta_2 \end{matrix}, \Sigma_1\right)$$

where the relationship between observed data y_{1i} and y_{2i}, and partially unobserved latent data y_{1i}^* and y_{2i}^* is as follows:

$$y_{1i} = \begin{cases} y_{1i}^* & if \quad y_{1i}^* > 0 \\ 0 & if \quad y_{1i}^* \le 0 \end{cases} \quad \text{and} \quad y_{2i} = \begin{cases} y_{2i}^* & if \quad y_{2i}^* > 0 \\ 0 & if \quad y_{2i}^* \le 0 \end{cases}.$$

The row vectors X_{1i} and X_{2i} are the observed covariates corresponding to the total transactions and total finance charges, respectively; the column vectors β_1 and β_2 are the corresponding coefficient vectors; and the 2×2 matrix Σ_1 is the variance-covariance matrix with three free parameters: two variances σ_{11} and σ_{22} and one covariance σ_{12}. The covariates of our interest are the following:

DM, INT, TS, DS = dummy variables indicating whether a customer was acquired by direct mail, Internet, telesales or direct selling respectively

REWARD = dummy variable (1=reward card holder, 0 otherwise)

AFFINITY = dummy variable (1=affinity card holder, 0 otherwise)

LIMIT = Credit limit that the bank approves for each customer.

Controlling for Endogeneity

In the above model, the decisions regarding the mode of acquisition, and whether to get a reward card or an affinity card are made by the customer presumably based on a cost-benefit analysis. Therefore these variables are not truly exogenous variables. The coefficient estimates for the affinity card dummy, the rewards card dummy, and the mode of acquisition dummy variables may be biased if the unobserved factors that influence a consumer's decision to choose one of these card features or modes of acquisition may be related to customer profitability.

Similarly, credit limit (LIMIT) is determined by the bank after an evaluation of the credit worthiness of the customer and so the credit limit cannot be treated as an exogenous variable. Further, in laboratory experiments, Soman and Cheema (2002) show that consumers with a higher credit limit increased their spending with the card indicating that unobserved factors which affect customer's evaluation of the credit limit could also affect their spending behavior. We therefore treat the variables DM, INT, TS, REWARD, AFFINITY and LIMIT as endogenous variables and estimate the entire system of equations as a simultaneous system. Of the above the first five dependent variables are binary and are estimated using probit specifications. LIMIT is modeled as a linear equation. Thus the full model is a complex system of equations with a bivariate tobit model, five probit models and a linear regression model, with errors of all equations being correlated with each other.

$$\begin{pmatrix} y_{1i}^* \\ y_{2i}^* \\ y_{3i} \\ y_{4i}^* \\ y_{5i}^* \\ y_{6i}^* \\ y_{7i}^* \\ y_{8i}^* \end{pmatrix} \sim N_8 \begin{pmatrix} X_{1i}\beta_1 + y_i^e \gamma_1 & \\ X_{2i}\beta_2 + y_i^e \gamma_2 & \\ X_{3i}\beta_3 & \\ X_{4i}\beta_4 & \\ X_{5i}\beta_5 & ,\Sigma \\ X_{6i}\beta_6 & \\ X_{7i}\beta_7 & \\ X_{8i}\beta_8 & \end{pmatrix},$$

where X_{1i} and X_{2i} include only the exogenously determined covariates, and the effect of the endogenous variables is captured by parameters γ_1 and γ_2 corresponding to the endogenous variable vector $y_i^e = (y_{3i}\, y_{4i}\, y_{5i}\, y_{6i}\, y_{7i}\, y_{8i})'$; and covariates $X_{ji}, j = 3,...,8$ include control variables and instrumental variables corresponding to the response variables $y_{ji}, j = 3,...,8$. The 8×8 variance-covariance matrix Σ has 36 elements, out of which we can identify 31 (five variances

$\sigma_{jj}, j = 4,...,8$, corresponding to the dummy variables $y_{ji}, j = 4,...,8$ are set to one). The relationship between observed data y_{ji}, and unobserved latent data $y^*_{ji}, j = 4,...,8$ is as follows:

$$y_{ji} = \begin{cases} 1 & if \quad y^*_{ji} > 0 \\ 0 & if \quad y^*_{ji} \leq 0 \end{cases}$$

The likelihood function involves the evaluation of a multivariate normal CDF of 5 to 7 dimensions for each individual. We employ Bayesian estimation methodology, which we describe briefly in the Appendix. Our estimation approach relies on the data augmentation framework of Albert and Chib (1993) and Tanner and Wong (1987).

5. Results

In tables 3a and 3b we report the estimates of two tobit models with customer profit as the dependent variable. In the first column, we present the estimates of the tobit model in which we do not control for endogeneity of the variables credit limit, rewards, affinity, DM, Internet and TS. In the second column we present estimates of the tobit model with proper control for endogeneity. The significance of the coefficients is measured at the 95% confidence level and is denoted by an asterisk. We find in the simple tobit model that affinity and reward card customers generate less profit than those without these cards. Further, direct mail customers are the most profitable, followed by internet customers (direct sell customers form the basis for comparison). Telesales and direct sell customers are not significantly different from each other with respect to profits.

When we properly control for endogeneity of some of the variables of interest, the results change significantly. It is important to treat the modes of acquisition and loyalty programs as endogenous because customers choose to participate through these programs. If the unobservable factors that affect the choice of mode of acquisition or the loyalty program also affect the customer usage (and hence profit) of the card, then the estimates of the simple model will be biased.

In the second column, with respect to the effect of different modes of acquisition on customer profit we see that direct mail customers appear to be the most profitable. We find that DM is better than Internet, consistent with our hypothesis H1a. We also find that DM customers are better than telesales customers and direct sell customers, providing support for hypotheses H1b and H1c. Contrary to our prediction in H1d, we find that the Internet customers are not significantly more profitable than direct sales customers. This result is different from that obtained from the simpler tobit model and confirms the magnitude of endogeneity bias. Telesales customers are significantly less profitable than the direct sell customers contrary to our hypothesis H1e. We had expected that since telesales allows the firm to target customers better than direct sales, it would yield relatively profitable customers. A possible explanation is that this firm is not being able to target profitable customers effectively using telesales. Thus, we have empirical support for three of the five hypotheses, that is, H1a, H1b, and H1c.

Regarding the effect of affinity and reward programs, we find that affinity card customers are less profitable than non-affinity card customers (β=-1.19). Note that this estimate for affinity card is significantly different (that is, about four times larger) than that obtained in the simpler model without control of endogeneity. Further, we see that there is no significant difference in profit between reward card customers and non-reward card customers (β=0.09), which is different from what we observed in the simpler tobit model. We find from the interaction effect (AFF*REW) that customers who have both affinity and reward cards have a higher profit relative to other customers. However, this positive effect is smaller than the direct negative effect of the affinity card and so that the net effect of the affinity card remains negative.

Regarding the effect of other covariates in the model, we find the estimates as expected. Older customers generate less profit than younger customers, and families with multiple cards from the same bank generate a higher profit. We also find that the profit is positively correlated with credit limit. This result is similar to that in Gross and Souleles (2002) who found that as the bank increases the credit limit, the customer debt on the card increases. We find that the type of card also has an effect on customer profit. Platinum card customers are the most profitable while the premium card customers generate the least profit (the basis for comparison is with respect to standard card holders). Premium card is a new program and is targeted at high income families and these families generate less profit. As expected, there are differences between different occupations and geographic location with respect to profit.

The estimates of the six endogenous variable equation models are reported in table 3b.

LIMIT: We see from the credit limit equation that older customers have higher credit limits. Further, students and unskilled labor have relatively lower limits (compared to the base group of retired customers) while higher income groups such as professionals, self employed, and skilled labor have higher limits. We see that customers with higher credit limits are likely to transact using their credit card earlier (i.e., have a smaller number of days to first retail transaction) but are reluctant to use the card to borrow (i.e. higher number of days to cash).

AFFINITY: Students, educators, professionals, preferred professionals, and military are more likely to have the affinity cards. Affinity card customers are less interested in rushing to use the card (lower DAYS2RTL) and are also slower to borrow cash relative to non affinity card members.

REWARDS: Affinity card holders appear to be less likely to have reward cards as seen by the negative sign on students and professionals. Reward cards appear to be used more by retired customers, homemakers, and others. Rewards do provide an incentive for customers to transact earlier though they may not borrow cash any sooner or later than non-reward customers.

Modes of acquisition: Students and professionals are more likely to be acquired through the Internet. Telesales appears to be the preferred mode of acquisition for homemakers and retired people. We see that DM customers and Internet customers use their card for transactions much earlier than TS and DS customers. TS customers have the longest delay consistent with the argument that they have the least need for the card. The above findings are consistent with intuition and provide a measure of the validity of the model. We defer a discussion of the variance covariance parameters reported in Table 3c until after the full model results are discussed.

In tables 4a and 4b, we present the estimates of the full model. The full model is a bivariate tobit model with two dependent variables transaction amount (TOTTRANS) and finance charges (TOTFC). In addition, we control for endogeneity of six variables. As stated earlier, there are two sources of profit – interchange fee (which is a percentage of the total transaction amount) and finance charges (interest on revolving balances). A major part of the bank's profit is due to finance charges. This model allows us to drill down and see the effect of the variables on the different sources of profit. We denote significance of estimates at the 95% level with an asterisk.

With respect to the relation between modes of acquisition and profits, we find that DM customers generate higher transaction amounts and higher finance charges for the bank than direct sell (DS) customers. Internet customers also generate higher transaction amounts than direct sell customers (significant at 90% confidence level) but do not generate significantly higher finance charges. Contrary to our expectation, telesales (TS) customers generate neither higher transaction amounts nor higher finance charges than DS customers. We had argued that even though both telesales and direct selling imposed a low level of effort on the part of the customer making an application for a credit card, telesales provided a better medium for targeting than direct sales efforts and so would yield better performance, on average. However, the negative and significant coefficients for TS suggest otherwise. This result also suggests that the targeting efforts of this bank using telesales may not be very effective. Thus our results support three of the five directional hypotheses (i.e., H1a, H1b, H1c) that we develop based on the interaction of the level of effort and ease of targetability. There is some weak support for Internet being a better mode than direct sales (H1d).

We find strong support for our hypothesis H2b but not for H2a. We find that affinity card holders generate less finance charges and less transaction volume than non-affinity card holders. Thus affinity card holders are less profitable, on average, than non-affinity card customers. The coefficients are negative and statistically significant at 95% confidence level (β = -1.36 and -10.41 respectively). The surprise is that affinity card does not even generate higher transaction amount and this evidence is counter to conventional wisdom about the effect of affinity program on usage. People sign up for an affinity card to derive psychological benefits from participation in their affinity group, and this perceived benefit may not lead to greater transaction amount. A possible reason for the prevalence of affinity card programs may be that the bank uses these to acquire new customers and not necessarily to generate higher profit. However, we are only studying the effect on profit.

With respect to the effect of rewards cards on customer behavior, we expected that reward cards would encourage greater spending on purchases (TOTTRANS) with the card but may not result in higher finance charges (TOTFC). In the full model, we do not find any significant difference between reward card holders and non-reward card holders for either measure at the 95% confidence level. Customers who had both affinity card and reward card exhibit higher transaction amounts and higher finance charges, on average. Thus we see that though the direct effect of the reward card is not significant, it has an indirect effect through the interaction term with affinity card. However, the net effect of the affinity card (considering both the direct and the interaction effect) on total transactions, and finance charges, is negative. This suggests that while the reward card may exert a positive effect on profitability it is not enough to offset the negative effect of the affinity card.

Since there is a possibility of interaction between modes of acquisition and loyalty programs, we included the interaction terms in the full model. We find that the interaction effect between modes of acquisition and reward card and between modes of acquisition and affinity card are not significant for the most part. There is evidence of a significant (at 90% level) interaction effect between rewards and telesales. This suggests that giving reward cards to customers acquired through direct sales generates higher transaction amounts than giving rewards cards to telesales customers.

The effects of age and credit limit are similar to the effects observed earlier with respect to profit. Older customers generate less interchange fee and less interest than younger customers. As the credit limit is increased, one would observe greater transaction amount as well as higher borrowing. When interpreting the effect of occupations on profit, the base level for comparison is against retired customers. We find that educators, professionals, self employed persons, skilled laborers, homemakers and military persons generate higher finance charges than retired people. We find that the top three largest borrowers comprise of homemakers, military and self employed persons.

In table 4b, we report the estimates of the endogenous equations. For the most part, the insights are similar to what we observed in table 3b and do not need repetition. The major takeaways are that DM and INT customers transact sooner than DS and TS customers. We had argued that these modes of acquisition involve more effort than TS and DS. Hence, DM and INT customers would perceive a greater benefit from using the card and therefore would use the card sooner. TS customers delay the longest in using their card for the first time, indicating a lack of interest in the card. These estimates provide support to our arguments about differences in perceived effort across different modes of acquisition. Affinity card customers have higher duration before they use the card for transaction or borrowing, indicating a lower level of interest in the card. The evidence suggests that the psychological benefit from getting an affinity card is not enough to impact their transactions in favor of the bank. This is a new finding. Past research has limited itself to the attitudinal benefits of affinity and has suggested that some of the attitude would transfer to the product. We find no evidence of such transfer of goodwill in the credit card market. In contrast, reward card holders transact sooner but do not borrow sooner.

Table 4c provides estimates of the covariances between the different equations. The covariance between the sources of profit is 40.12 and significant, indicating the need for a bivariate tobit model specification. Similarly, the covariances between the modes of acquisition and the sources of profit are significantly different from zero supporting the need for joint estimation of these equations. These values support our choice of the more complicated joint model.

6. Conclusions, Limitations and Directions for Future Research

Firms need to have a thorough understanding of the relationship between customer acquisition and retention strategies, and customer profitability. This knowledge will allow managers to make better decisions regarding the types of customers to retain and thus allocate direct marketing resources more efficiently. Our study seeks to quantify the impact that relationship marketing has on customer profitability using a proprietary dataset from a financial services company. In addition to profits, we understand the effect of acquisition and retention strategies on the sources of profit, namely, transaction amount and finance charges.

We use both univariate and bivariate Tobit model specifications, with proper controls for endogeneity of credit limit as well as for modes of acquisition and retention strategies. We estimate the models using data on transactions over a 36 month period of 8802 customers who obtained accounts at the same time. Our results show that direct mail and Internet modes of acquisition generate more profitable customers than direct selling or telesales. This is consistent with three of our five hypotheses developed by considering the effects of customer effort as well as the ease of targetability in using different modes of acquisition. Based on these findings, managers will be able to allocate resources across the four modes of acquisition in a more effective manner. Note that we do not study the effectiveness of the different modes of acquisition with respect to acquiring customers. It is conceivable that DS and TS are used by banks to generate a larger number of new accounts, in spite of their lower expected profits. This is a potential area for further research.

In our study we find strong evidence that affinity and reward programs generate less profit on average relative to customers who do not have these programs, either by attracting the less profitable customers or by rewarding customers for the less rewarding behavior i.e.

increasing transaction amounts. These findings are contrary to current research and popular beliefs regarding the effectiveness of such programs. Much of the theory supporting affinity programs posits an enhanced loyalty effect, which in turn is expected to lead to higher profits. At least in the credit card industry, our results indicate otherwise. Not only do affinity program members generate lesser profits, they also generate lower transaction amounts. Thus the evidence does not support the popular belief that affinity leads to greater usage. This suggests that managers need to critically examine the role of these programs and see how they can be improved. It is conceivable that affinity programs build loyalty and reduce churn, which could then affect long term profits or lifetime value. We have not assessed the effect of affinity on either customer lifetime or the probability of acquisition and we leave it as important areas for future research. Consistent with prior research, we do find that reward cards increase the transaction amounts (usage) but do not generate higher profits. Our research suggests the need to examine the costs of such programs and see if the affinity and reward programs can be administered more efficiently.

We show that there is substantial bias by assuming that the modes of acquisition, loyalty cards and credit limit are exogenous. Past studies have not addressed the issue of selection bias in a rigorous manner and our study contributes by developing a model and estimating it using hierarchical Bayesian methods. We believe that future models of CRM should seriously consider the potential bias due to the fact that some of the decisions (choice of mode or type of loyalty card) are made by the customer who is also engaging in the transaction.

In the current measure of profitability, we used aggregate averages of costs in the calculation, due to data limitations. For instance, the costs of the affinity programs and reward programs are calculated based on a fixed average percentage of transaction amount. In that sense, we are not measuring true customer profit. However, banks have access to more detailed cost information and can benefit from our model specification to assess the profit impact of such programs better. We believe that the substantial results will not change in direction but only in magnitude. Similarly, we do not employ a measure of customer lifetime value (CLV) as our dependent variable because it involves computing the lifetime of a customer who may observe silent attrition. There are models such as the Pareto-NBD which have been used in the literature to compute the CLV (Reinartz and Kumar 2003). We believe that our substantial results would not change.

A second data limitation that must be overcome for a truly accurate picture of customer-level profitability is how to handle multiple accounts. Since some customers carry multiple cards with the same firm it is possible that the household level profitability is different from individual customer profitability. The current dataset does not contain information on second or third accounts because the database does not link accounts by a customer-level identifier nor contain any personally identifiable information. A further limitation of our study is that we do not have data on other firm's credit cards in a customer's wallet. If we know the share of wallet of each customer, even a customer who is currently unprofitable can be considered attractive based on potential transactions and could be targeted. It is important to estimate the share of wallet in addition to profits to be able to target customers better. Because we have data on only 36 months of activity, one can argue that our results could change if we had a longer period of data. Thus there might be a bias due to right censoring of data. However, we believe that there is no systematic bias and while the magnitude of the estimates may change somewhat, the direction of the results would not.

Despite these limitations, this is the first paper to examine the effect of affinity programs on customer profit. It also provides non-intuitive results with respect to the effect of rewards cards and modes of acquisition in the credit card markets. We hope that our research will provoke additional research and also address some of the above limitations.

References

Albert, J. and S. Chib (1993), "Bayesian Analysis of Binary and Polychotomous Response Data," *Journal of the American Statistical Association*, Vol. 88, No. 422, 669-679.

Berger, Paul D. and Nada I. Nasr (1998), "Customer Lifetime Value: Marketing Models and Applications, *Journal of Interactive Marketing*, 12 (1), 17-30.

Blattberg, Robert C. and John Deighton (1996) "Manage Marketing by the Customer Equity Test," *Harvard Business Review*, July/August, p. 136-144.

Blattberg, Robert C., Gary Getz, and Jacquelyn S. Thomas (2001), Customer Equity: *Building and Managing Relationships as Valuable Assets*, Boston: Harvard Business School Press.

Bolton, Ruth, P.K. Kannan and M.D. Bramlett (2000), "Implications of Loyalty Program Membership and Service Experiences for customer Retention and Value," *Journal of the Academy of Marketing Science*, 28 (1), 95-108.

Bolton, R.N., K.N. Lemon and P.C. Verhoef (2004), "The Theoretical Underpinnings of Customer Asset Management: A Framework and Propositions for Future Research," Journal of the Academy of Marketing Science, Vol. 32, No. 3, 271-292

http://www.cardweb.com/cardtrak/news/2004/february/13a.html

http://www.cardweb.com/cardtrak/news/2005/january/13a.html

Cardozo, Richard N. (1965), "An Experimental Study of Consumer Effort, Expectation, and Satisfaction," *Journal of Marketing Research*, 2, 244-249.

Clarke, Keith and Russell Belk (1979), "The Effect of Product Involvement and Task Definition on Anticipated Consumer Effort," *Advances in Consumer Research*, 6 (1), 313-318.

Dowling, Grahame R. and Mark Uncles (1997), "Do Customer Loyalty Programs Really Work?" *Sloan Management Review*, 38, (Summer), p. 71-82.

Drèze, Xavier and Stephen J. Hoch, (1998), "Exploiting the Installed Base Using Cross-Merchandising and Category Destination Programs," *International Journal of Research In Marketing*, 1998, Vol. 15 (5), p. 459-471.

Dwyer, F. Robert (1997), "Customer Lifetime Valuation to Support Marketing Decision Making," *Journal of Direct Marketing,* 11 (Fall), 6-13.

East, Robert, A. Hogg and Wendy Lomax (1998), "The Future of Retail Loyalty Schemes," *Journal of Targeting, Measurement and Analysis for Marketing*, 7, 1, p. 11-21.

Fornell, Claes and Birger Wernerfelt (1987), "Defensive Marketing Strategy by Customer

Complaint Management: A Theoretical Analysis," *Journal of Marketing Research*, 24, November, p. 337-346.

Garcia, Gillian (1980), "Credit Cards: An Interdisciplinary Study," *Journal of Consumer Research*, 6 (March), 327-337.

Gross, David B., and Nicholas S. Souleles (2002), "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data," *Quarterly Journal of Economics*, 117, 149-185.

Hartmann and Viard (2008), "Do Frequency Reward Programs Create Switching Costs? A Dynamic Structural Analysis of Demand in a Reward Program" *Quantitative Marketing and Economics*, 6 (2), 109-137.

Heskett, James L., W. Earl Sasser Jr., and Leonard A.Schlesinger (1997), *The Service Profit Chain: How Leading Companies Link Profit and Growth to Loyalty, Satisfaction, and Value*, New York, NY: The Free Press.

Keane, T.J. and P. Wang (1995) "Applications for the Lifetime Value Model in Modern Newspaper Publishing," *Journal of Direct Marketing*, 9 (2), p. 59-66.

Kim, Byung-Do, Mengze Shi, and Kannan Srinivasan (2001), "Reward Programs and Tacit Collusion," *Marketing Science*, 20 (2) Spring, p. 99-120.

Kivetz, Ran and Itamar Simonson (2002), "Earning the Right to Indulge: Effort as a Determinant of Customer Preferences Toward Frequency Reward Programs," *Journal of Marketing Research*, 39 (May), 155-170.

Klemperer, Paul (1987), "The Competitiveness of Markets with Switching Costs," *Rand Journal of Economics*, 18 (1) Spring, 138-150.

Kopalle, Praveen K. and Scott A. Neslin (2003), "The Economic Viability of Frequency Reward Programs in a Strategic Competitive Environment," *Review of Marketing Science*, 1(1).

Kumar, V. and Werner J. Reinartz (2006), *Customer Relationship Management: A Databased Approach*, Hoboken, NJ: John Wiley and Sons, Inc.

Lal, Rajiv and David E. Bell (2003), "The Impact of Frequent Shopper Programs in Grocery Retailing," *Quantitative Marketing and Economics*, 1, p. 179-202.

Lee, W.A. (2001), "Credit Card Profitability Improved Again Last Year," *American Banker*, 166, 6, p. 10.

Lewis, Michael (2004), "The Influence of Loyalty Programs and Short-Term Promotions on Customer Retention," *Journal of Marketing Research*, 41(3), 281-292.

Liu, Yuping (2007), "The Long-Term Impact of Loyalty Programs on Consumer Purchase Behavior and Loyalty," *Journal of Marketing*, 71(4), 19-35.

Machiette, Bart and Abhijit Roy (1992), "Affinity Marketing: What is it and how does it Work," *Journal of Services Marketing*, 6 (3), 47-58.

Mathur, Anil and George P. Moschis (1994), "Use of Credit Cards by Older Americans," *Journal of Services Marketing*, 8, 1, p. 27-36.

Mathews, H. Lee and John W. Slocum (1969), "Social Class and Commercial Bank Credit Card Usage," *Journal of Marketing*, 33 (January), p. 71-78.

McGeehan, Patrick (2004), "Soaring Interest Compounds Credit Card Pain for Millions," *The New York Times*, November 21, 2004.

Min, Insik and Jong-Ho Kim (2003), "Modeling Credit Card Borrowing: A Comparison of Type I and Type II Approaches," *Southern Economic Journal*, 70 (1), p. 128-143.

Morgan, R.M. and S. D. Hunt (1994), "The Commitment-Trust Theory of Relationship Marketing," *Journal of Marketing*, 58 (July), p. 30-37.

Mulhern, Francis (1999), "Customer Profitability Analysis: Measurement Concentration, and Research Directions," *Journal of Interactive Marketing*, 13 (1), p. 25-40.

Nichols, D. (1990), "Promoting the Cause," *Incentive,* August, 28-31.

O'Brien, Louise, and Charles Jones (1995), "Do Rewards Really Create Loyalty?" *Harvard Business Review*, 73 (May-June), 75-82.

Perrien, Jean, Pierre Filiatrault, and Ricard Line (1992), "Relationship Marketing and Commercial Banking: A Critical Analysis," *The International Journal of Bank Marketing*, 10 (7), 25-29.

Reichheld, Frederick F. (1993), "Loyalty-Based Management," *Harvard Business Review*, March-April, 64-73.

Reichheld, Frederick F. and W. Earl Sasser (1990), "Zero Defections: Quality Comes to Services," *Harvard Business Review*, September-October, p. 105-111.

Reinartz, Werner J. and V. Kumar (2000), "On the Profitability of Long-Life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing," *Journal of Marketing*, 64 (October), 17 – 35.

Reinartz, Werner J. and V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration," *Journal of Marketing*, 67 (January), 77-99.

Reinartz, Werner J, Jacquelyn S. Thomas and V. Kumar (2005), "Balancing Acquisition and Retention Resources to Maximize Profitability," *Journal of Marketing*, 69 (January), 63-79.

Rust, Roland T., Valerie A. Zeithaml, and Katherine N. Lemon (2000), *Driving Customer Equity: How Customer Lifetime Value is Reshaping Corporate Strategy,* New York, NY: The Free Press.

Rust, Roland T., Katherine N. Lemon, and Valerie Ziethaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (January), 109-127.

Schlegelmilch, Bodo B. and Helen Woodruffe (1995), "A Comparative Analysis of the Affinity Card Market in the USA and the UK," *International Journal of Bank Marketing*, 13, 5, p. 12-23.

Sharp B., and Sharp A. (1997), "Loyalty Programs and their Impact on Repeat-purchase Loyalty Patterns," *International Journal of Research in Marketing*, 14 (5), 473-487.

Sheth, Jagdish N. and Rajendra Sisodia (1995), "Improving the Marketing Productivity," in *Encyclopedia of Marketing for the Year 2000*, Chicago, IL: American Marketing Association – NTC Publishing.

Swaminathan, V. and Srinivas K. Reddy (2000), "Affinity Partnering: Conceptualization and Issues," in *Handbook of Relationship Marketing*, Jagdish N. Sheth and Atul Parvatiyar eds. Thousand Oaks, CA: Sage, 381-405.

Tanner, M.A. and W.H. Wong (1987), "The Calculation of Posterior Distributions by Data Augmentation," *Journal of the American Statistical Association*, Vol. 82 (398), 528-540.

Thomas, Jacquelyn S. (2001) "A Methodology for Linking Customer Acquisition to Customer Retention," *Journal of Marketing Research,* 38 (May), p. 262-268.

Venkatesan, Raj and Kumar, V. (2004), "A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy," *Journal of Marketing*, 68 (October), 106-125.

Verhoef, P.C. and Bas Donkers (2005), "The effect of acquisition channels on customer loyalty and cross-buying," *Journal of Interactive Marketing,* 19 (2), 31-43.

Wayland, R. E. and P.M. Cole (1997), *Customer Connections: New Strategies for Growth*, Boston: Harvard Business School Press.

Woo, K., H. K. Y. Fock and M. K. M. Hui (2006), "An Analysis of Endorsement Effects in Affinity Marketing: The Case for Affinity Credit Cards," *Journal of Advertising*, 35(3), 103-113.

Worthington, Steve and Suzanne Horne (1998), "A New Relationship Marketing Model and Its Application in the Affinity Credit Card Market," *International Journal of Bank Marketing,* 61 (1), 39-44.

Worthington, Steve (2001a), "Affinity Credit Cards: A Critical Review," *International Journal of Retail and Distribution Management*, 29 (11), p. 485-492.

Wyner, G. A. (1996), Customer Profitability: Linking Behavior to Economics, *Marketing Research*, 8 (2), p. 36-38.

Table 1: Major Findings from Relevant Research

Study	Focus of study	Data/Model	Key Results/Remarks
Venkatesan and Kumar (2004)	How much to invest in different channels for ongoing relationships	B2B Computer hardware	Marketing contacts affect CLV in an Inverted U shape (nonlinear) fashion.
Verhoef and Donkers (2005)	Impact of acquisition channels on loyalty and cross buying	Insurance industry/probit model	Direct mail/TV, radio worst channels with respect to retention probability. Co-insurance and outbound telephone are best.
Rust and Verhoef (2005)	How to design mix of interventions for each customer	Insurance industry	Relationship intervention more effective with loyal customers. Action oriented intervention more effective with non-loyals. Loyalty program members respond positively to CRM interventions.
Bolton, Lemon and Verhoef (2004)	Theoretical framework		
Reinartz, Thomas, and Kumar (2005)	Modes of contacts and effect on probability of acquisition, profit, and lifetime (duration)	B2B - High tech co.	Face-to-face > telephone > email contacts with respect to probability of acquisition, duration, and profitability.
Bolton (2004)	Acquisition channels and loyalty		Channels that focus on price (DM) generate less loyal customers. Mass media and WOM lead to higher loyalty. Internet customers more loyal.
Keane and Wang (1995)			Acquisition channel affects LTV
Thomas (2001)			Acquisition channel affects retention

Rewards cards

Study	Context	Key Results/Remarks
Sharp and Sharp (1997)	Australia FlyBuys program	Weak effect of LP on repeat purchase rates
Dreze and Hoch (1998)	Baby products	LP increases category sales and store traffic
Bolton, Bramlett and Kannan (2000)	Credit cards	No effect on retention. LP members increases usage of card and forgive the firm for any negative experiences.
Lewis (2004)	Online grocer	Loyalty program (LP) increases annual purchasing for a substantial percentage of customers
Verhoef (2003)	Insurance	LP members more likely to stay with firm and cross buy more.
Liu (2007)	Grocery chain reward program	LP affects purchase behavior for light buyers but not heavy buyers. Light buyers purchase more, become more loyal and cross buy more.
Reinartz and Kumar (2003)	Catalog retailer	LP members have a higher profitable lifetime duration. Here loyalty program refers to owning a free charge card of the store (unlike a reward card)

Table 2: Descriptive Statistics (N=8802)

Variable	Mean	Standard Deviation
PROFIT	0.847	1.35
TOTAL TRANSACTION	11.45	19.76
TOTAL FINANCE CHARGE	0.83	1.51
CARD COUNT	1.26	0.45
CREDIT LIMIT	12.28	8.11
AGE	45.90	14.59
AFFINITY	0.83	0.37
REWARDS	0.20	0.40
AFF * REW	0.11	0.31
DIRECTMAIL	0.42	0.49
INTERNET	0.05	0.22
TELESALES	0.40	0.49
DIRECT SELLING	0.13	0.34
STANDARD	0.17	0.37
GOLD	0.02	0.13
PLATINUM	0.75	0.43
PREMIUM	0.06	0.24
RETIRED	0.09	0.28
STUDENT	0.09	0.29
EDUCATOR	0.05	0.23
PREF_PROF	0.09	0.28
PROF	0.28	0.44
SELF_EMPL	0.09	0.29
SKILL_LABOR	0.20	0.40
UNSKILL_LAB	0.04	0.20
OTHER	0.04	0.18
HOMEMAKER	0.02	0.14
MILITARY	0.01	0.07

Table 2b: Coefficient of variation by mode of acquisition

	Direct mail	Direct selling	Internet	Telesales
Profit	1.34	1.76	1.43	1.89
Trans. Amount	1.45	1.91	1.35	1.89
Fin. Charges	1.54	2.02	1.69	2.02

Table 3a: Estimates of the tobit model and tobit model with endogeneity

Dependent variable = profit

Variable	Tobit Model Coefficients	Tobit model with endogeneity Coefficients
Constant	0.87 *	0.94 *
LIMIT	0.00 *	0.04 *
AFFINITY	-0.29 *	-1.19 *
REWARDS	-0.37 *	0.09
AFF * REW	0.16	0.41 *
DIRECTMAIL	0.48 *	1.85 *
INTERNET	0.23 *	0.05
TELESALES	0.03	-1.33 *
CARD_COUNT	0.09 *	0.10 *
AGE	-0.01 *	-0.02 *
GOLD	0.12	0.05
PLATINUM	0.29 *	0.25 *
PREMIUM	-0.38 *	-0.46 *
STUDENT	-0.12	0.25
EDUCATOR	0.34 *	0.47 *
PREF_PROF	0.46 *	0.04
PROF	0.48 *	0.24 *
SELF_EMPL	0.44 *	0.36 *
SKILL_LABOR	0.18 *	0.08
UNSKILL_LAB	0.02	0.07
OTHER	-0.01	-0.15
HOMEMAKER	0.23 *	0.70 *
MILITARY	0.66 *	0.77 *
MOUNTAIN	-0.06	-0.11
WN_CENTRAL	-0.24 *	-0.26 *
EN_CENTRAL	-0.17 *	-0.19 *
WS_CENTRAL	0.07	0.08
ES_CENTRAL	-0.01	-0.06
SOUTH_ATL	-0.02	-0.02
NEW_ENG	-0.07	-0.06
MID_ATL	-0.18 *	-0.20 *

Table 3b: Estimates of the six endogenous equations (Dependent variable = Profit)

	Limit	Affinity	Rewards	DM	INT	TS
Constant	5.66 *	0.94 *	-0.83 *	0.25 *	-1.49 *	-1.31 *
AGE	0.11 *	-0.01 *	0.01 *	0.01 *	-0.02 *	0.01 *
STUDENT	-2.26 *	0.47 *	-0.63 *	-0.16	0.65 *	-0.43 *
EDUCATOR	4.74 *	0.31 *	-0.18 *	-0.10	0.46 *	0.05
PREF_PROF	8.52 *	0.46 *	-0.29 *	0.56 *	0.56 *	-0.43 *
PROF	5.43 *	0.15 *	-0.25 *	0.36 *	0.54 *	-0.28 *
SELF_EMPL	4.01 *	-0.25 *	-0.08	0.18 *	0.13	0.06
SKILL_LABOR	2.04 *	-0.10	-0.12	0.17 *	0.45 *	-0.23 *
UNSKILL_LAB	-0.81	-0.20 *	0.00	0.03	0.35	-0.05
OTHER	0.03	-0.53 *	0.19 *	0.20	0.06	0.06
HOMEMAKER	1.63 *	-0.15	0.02	-0.45 *	-0.17	0.62 *
MILITARY	0.96	0.31	-0.18	-0.16	1.33 *	-0.20
DAYS2RTL	-2.18 *	0.14 *	-0.28 *	-0.94 *	-0.60 *	0.98 *
DAYS2CASH	-0.40 *	0.50 *	-0.10	-0.80 *	0.40 *	0.50 *

Table 3c: Upper triangular matrix of the Variance–Covariance matrix showing dependence between equations

	PROFIT	TS	INT	DM	Rewards	Affinity	Limit
PROFIT	3.62	1.07	0.17	-1.11	-0.60	0.74	-2.19
TS		1	0.03	-0.53	-0.21	0.25	-0.37
INT			1	-0.17	0.07	0.04	-0.10
DM				1	0.21	-0.30	0.59
Rewards					1	-0.33	0.41
Affinity						1	-0.48
Limit							53.74

Table 4a: Estimates of the Full Model (Bivariate Tobit Model estimates)

VARIABLE NAME	TOTTRANS	TOTFC
Constant	-3.75	0.26
LIMIT	1.59 *	0.05 *
AFFINITY	-10.41 *	-1.36 *
REWARDS	4.63	-0.23
AFF * REW	6.27 *	0.62 *
DIRECTMAIL	26.43 *	2.82 *
INTERNET	9.88 [b]	0.44
TELESALES	-13.02 *	-1.47 *
CARD_COUNT	4.94 *	0.09
AGE	-0.25 *	-0.02 *
GOLD	-2.48	0.02
PLATINUM	-0.26	0.33 *
PREMIUM	-9.39 *	-0.75 *
STUDENT	3.34 [b]	0.58 *
EDUCATOR	-3.20 [b]	0.81 *
PREF_PROF	-6.22 *	0.24
PROF	-3.54 *	0.53 *
SELF_EMPL	0.26	0.67 *
SKILL_LABOR	-4.30 *	0.37 *
UNSKILL_LAB	-2.18	0.30
OTHER	-1.29	-0.04
HOMEMAKER	5.99 *	1.07 *
MILITARY	-4.13	1.08 *
MOUNTAIN	-0.68	-0.14
WN_CENTRAL	-2.46 [b]	-0.39 *
EN_CENTRAL	-2.28 *	-0.27 *
WS_CENTRAL	-0.76	0.13
ES_CENTRAL	-3.53 *	-0.02
SOUTH_ATL	0.42	0.02
NEW_ENG	1.36	-0.11
MID_ATL	-1.55 [b]	-0.28 *
AFFINITY-DIRECTMAIL	-2.11	-0.31
AFFINITY-INTERNET	-1.48	-0.23
REWARDS-DIRECTMAIL	-1.48	0.27
REWARDS-INTERNET	-3.68	-0.02
REWARDS-TELESALES	-6.15 [b]	0.12

* denotes that the estimate is significant at the 95% confidence level.
[b] denotes that the estimate is significant at the 90% confidence level.

Table 4b: Estimates of the Endogenous variable equations of the Full model

	Limit	Affinity	Rewards	DM	INT	TS
Constant	5.71 *	0.94 *	-0.83 *	0.25 *	-1.49 *	-1.30 *
AGE	0.11 *	-0.01 *	0.01 *	0.01 *	-0.02 *	0.01 *
STUDENT	-2.28 *	0.47 *	-0.64 *	-0.15	0.63 *	-0.43 *
EDUCATOR	4.70 *	0.30 *	-0.18 *	-0.10	0.43 *	0.05
PREF_PROF	8.49 *	0.45 *	-0.28	0.56 *	0.53 *	-0.42 *
PROF	5.39 *	0.15 *	-0.25 *	0.36 *	0.52 *	-0.27 *
SELF_EMPL	3.99 *	-0.25 *	-0.07	0.18 *	0.13	0.06
SKILL_LABOR	2.02 *	-0.10	-0.12 [b]	0.17 *	0.44 *	-0.23 *
UNSKILL_LAB	-0.82 [b]	-0.21 *	0.003	0.04	0.32	-0.05
OTHER	0.02	-0.53 *	0.19 *	0.21 *	-0.003	0.05
HOMEMAKER	1.62 *	-0.16	0.02	-0.43 *	-0.09	0.62 *
MILITARY	0.95	0.28	-0.19	-0.17	1.32 *	-0.20
DAYS2RTL	-2.31 *	0.14 *	-0.29 *	-0.96 *	-0.61 *	1.01 *
DAYS2CASH	-0.40 *	0.50 *	-0.10	-0. 80 *	0.40 *	0.50 *

* denotes that the estimate is significant at the 95% confidence level.
[b] denotes that the estimate is significant at the 90% confidence level.

Table 4c: Upper triangular matrix of Variance–Covariance matrix showing dependence between equations

	TOTTRA	TOTF	TS	INT	DM	Rewar	Affinity	Limit
TOTTRA	649.39	40.12	11.74	1.27	-11.90	-6.25	7.40	-28.56
TOTFC		6.56	1.35	0.22	-1.41	-0.73	0.93	-2.89
TS			1	0.03	-0.53	-0.21	0.25	-0.37
INT				1	-0.16	0.07	0.04	-0.10
DM					1	0.21	-0.30	0.60
Rewards						1	-0.33	0.42
Affinity							1	-0.49
Limit								53.77

Note that all estimates are significant at 95% confidence levels except two marked (ns).

APPENDIX A

Brief description of the estimation procedure for the joint model

To simplify the description of our estimation methodology, we need to define several additional variables. Let the observed data be denoted by $y_i = \left(y_{1i}\, y_{2i}\, y_{3i}\, y_{4i}\, y_{5i}\, y_{6i}\, y_{7i}\, y_{8i}\right)'$, the latent data by $y_i^* = \left(y_{1i}^*\, y_{2i}^*\, y_{3i}\, y_{4i}^*\, y_{5i}^*\, y_{6i}^*\, y_{7i}^*\, y_{8i}^*\right)'$, and the parameters by $\beta = (\beta_1 \gamma_1 \beta_2 \gamma_2 \beta_3 \beta_4 \beta_5 \beta_6 \beta_7 \beta_8)'$.

We denote the free elements in Σ by a vector ψ (as we mentioned in the model description section, the free elements include all covariance parameters, and 3 identifiable variances). Finally, if we let $X_i = \begin{pmatrix} X_{1i} & y_i^e & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & X_{2i} & y_i^e & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & X_{3i} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & X_{4i} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & X_{5i} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{6i} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{7i} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{8i} \end{pmatrix}$,

then the likelihood contribution for individual *i* equals

$p(y_i \mid \beta, \psi) = \int_{A_1}\int_{A_2}\int_{A_4}\cdots\int_{A_8} N_8\left(y_i^* \middle| X_i\beta, \Sigma\right) dy_1^* dy_2^* dy_4^* \ldots dy_8^*$, where the limits of integration correspond to the constraints imposed by the relationship between the observed data and the unobserved latent data. This expression means that we have to evaluate the multivariate normal cdf of 5 to 7 dimensions for each individual in our dataset to find the MLE estimates. To avoid calculating these integrals, we employ Bayesian estimation methodology. Our estimation approach relies on the data augmentation framework of Albert and Chib (1993) and Tanner and Wong (1987), which implies that the full joint posterior distribution for this model is defined as

$$p(y^*,\beta,\psi \mid y) \propto p(\beta)p(\psi)\prod_{i=1}^{N} \begin{matrix} \left[1(y_{1i}=0)1(y_{1i}^*<0)+1(y_{1i}>0)1(y_{1i}^*=y_{1i})\right]\times \\ \left[1(y_{2i}=0)1(y_{2i}^*<0)+1(y_{2i}>0)1(y_{2i}^*=y_{2i})\right]\times \\ \prod_{j=4}^{8}\left[1(y_{ji}=0)1(y_{ji}^*<0)+1(y_{ji}=1)1(y_{ji}^*>0)\right]\times \\ N_8\left(y_i^* \middle| X_i\beta,\Sigma\right). \end{matrix}$$

Here, the vector $y^*=(y_1^* y_2^* \dots y_N^*)'$, $p(\beta)$ is the prior for β, and $p(\psi)$ is the prior for ψ. We can construct the Markov chain by specifying the following full conditional distributions:

- $y_i^* \mid y_i, y_{-i}^*, \beta, \psi, \quad i=1,\dots,N$
- $\beta \mid y^*, \psi$
- $\psi \mid y^*, \beta,$

where y_{-i}^* is the set of all elements in y^* with the exception of y_i^*.

To help with the identification of the model parameters, we specify a weakly informative multivariate normal prior for the parameters in ψ, centered at the least squares estimates for $\sigma_{11},\sigma_{12},\sigma_{22}$ and σ_{33}, and zeros for the remaining covariances, $p(\psi) \sim N_{31}(g_0, G_0)$. We chose a non-informative, uniform prior for β.

The first step in our MCMC simulation is a multivariate truncated normal distribution:

$$p(y_i^* \mid y_i,\beta,\psi) \propto \begin{matrix} \left[1(y_{1i}=0)1(y_{1i}^*<0)+1(y_{1i}>0)1(y_{1i}^*=y_{1i})\right]\times \\ \left[1(y_{2i}=0)1(y_{2i}^*<0)+1(y_{2i}>0)1(y_{2i}^*=y_{2i})\right]\times \\ \prod_{j=4}^{8}\left[1(y_{ji}=0)1(y_{ji}^*<0)+1(y_{ji}=1)1(y_{ji}^*>0)\right]\times \\ N_8\left(y_i^* \middle| X_i\beta,\Sigma\right) \end{matrix}$$

for each *i=1,…,N*. We sample unobserved elements in y_i^*, one at a time, using the inverse CDF method, by simulating from a univariate truncated normal distribution conditioned on all the other elements in y_i^* from the joint distribution specified above.

The second step in the MCMC procedure is a multivariate normal distribution:

$p(\beta \mid y^*, \psi) \propto N_k(\bar{\beta}, \bar{B})$, where k is the total number of covariates in the model, and

$\bar{B} = \left(\sum_{i=1}^{N} X_i' \Sigma^{-1} X_i\right)^{-1}$ and $\bar{\beta} = \left(\sum_{i=1}^{N} X_i' \Sigma^{-1} X_i\right)^{-1} \left(\sum_{i=1}^{N} X_i' \Sigma^{-1} y_i^*\right)$.

The last distribution is proportional to $p(\psi \mid y^*, \beta) \propto N_{31}(g_0, G_0) \prod_{i=1}^{N} N_8\left(y_i^* \middle| X_i \beta, \Sigma\right)$ restricted to the region that generates a positive-definite covariance matrix Σ. This posterior distribution is not of standard form and is sampled by the Metropolis-Hastings algorithm. Briefly, we use the method of tailoring proposed by Chib and Greenberg (1995) using an independence chain with a multivariate-t proposal distribution with parameters equal to the mode and Hessian of the log of the conditional density above. A more detailed description of this step in a similar application is available in Chib, Seetharaman, and Strijnev (2002).

Chib, Siddartha and Edward Greenberg (1995), "Understanding the Metropolis-Hastings Algorithm," *The American Statistician*, 49 (4), 327-335.

Chib, S., P.B. Seetharaman and A. Strijnev (2002), "Analysis of Multi-Category Purchase Incidence Decisions Using IRI Market Basket Data," *Advances in Econometrics*, 16, 55–90.