ELSEVIER

Journal of Retailing 84 (1, 2008) 15–27

Journal of Retailing

Cross-buying in retailing: Drivers and consequences

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Abstract

The phenomenon of cross-buying by consumers enables retailers to cross-sell their products and increase revenue contribution from existing customers. The effectiveness of cross-selling can be greatly improved by identifying the drivers of cross-buy and using them to target the right customers. In this study we identify exchange characteristics such as average interpurchase time, ratio of product returns, and focused buying, and product characteristics such as category of first purchase, as important drivers of cross-buy. The impact of marketing efforts of the firm on cross-buy is also identified. The results of the study have important implications for academicians in understanding what drives cross-buying as well as practitioners to help design more effective cross-selling strategies.

Keywords: Cross-buying; Marketing efforts; Random coefficient seemingly unrelated regression model

Introduction

Consumer goods giant Unilever has recently launched a direct marketing initiative to cross-sell several of its food brands like PG Tips, Hellmann's, Chicken Tonight, Knorr, and Flora. In principle, this initiative is similar to Golden Households, which Unilever's rival, Procter & Gamble, launched to cross-promote 16 products. Following in the footsteps of Amazon, many retail banks and financial service firms are trying out various cross-promotions to sell additional products and services and thereby expand the relationship with their existing customers. Cross-selling gives companies an opportunity to increase the revenue contribution from their existing customers. In many cases (especially services) cross-selling is an easier option for companies to grow compared to acquisition of new customers (Felvey 1982).

Academic research has identified the importance of cross-selling in different facets of customer relationship and customer value. Effective cross-selling of multiple products or services enhances customer retention because customer switching costs increases with increased cross-buying. Blattberg et al. (2001) identified the return on cross-selling (or add-on-selling) as one of the three components of customer equity. Reinartz and Kumar (2003) found that customers who buy multiple product categories from a firm tend to have longer profitable lifetime duration. Cross-buying is also an important driver of customer lifetime value (Venkatesan and Kumar 2004) and multi-channel shopping behavior (Kumar and Venkatesan 2005), which in turn, leads to higher revenues, higher share of wallet, and higher customer value.

Despite the importance of cross-selling for customer retention and customer value, limited research has been done to identify the drivers of cross-buying. With the limited resources available with firms to allocate for different marketing activities such as retention and cross-selling, it is not possible to target all existing customers for cross-selling. Neither is it wise to spend marketing resources on all the customers because, not all customers are likely to cross-buy. This makes it imperative for firms to identify customers who have higher propensity to cross-buy so as to maximize their return on investments in various marketing activities especially cross-selling. Identifying the customers who are most likely to cross-buy is the first and most important step in developing a cross-sell strategy.

A limited number of studies in the past (Kamakura et al. 1991; Verhoef et al. 2001; Ngobo 2004) addressed the question of identifying customers who are likely to cross-buy. Other relevant studies include a next-product-to-buy (NPTB) model (Knott et al. 2002) and a model to predict the best way to sell the right

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doi:10.1016/j.jretai.2008.01.007

product to the right customer at the right time (Kumar et al. 2006). These studies give us insights on the drivers of cross-buy identified in the context of a service industry.

In the case of services, the relationship is often contractual with higher switching costs. The customer often acquires the products/services in a natural sequence, for example, in financial services a checking account will often precede a mortgage or a loan. On the contrary, in a non-contractual setting such as retailing, the switching cost is often very insignificant and the natural sequence of product acquisition is less apparent. Because of these differences, we expect the drivers of cross-buy for retailing to be different from that of a contractual service-based relationship. Reinartz and Kumar (2000) also caution that the theoretical findings with respect to customer relationships in a contractual setting may not hold good in a non-contractual setting. Moreover, some of the drivers identified in earlier studies such as satisfaction, payment equity (Verhoef et al. 2001), and perception of quality (Ngobo 2004) were evolved from survey-based studies. The need to collect primary data to measure these drivers often limits their use for identifying customers for cross-selling opportunities across the entire customer database. On the other hand, most firms collect and maintain a wealth of secondary data on customer purchase behavior and firm–customer interactions, which could potentially serve as a good source for uncovering different aspects of the customer's relationship with the firm including the drivers of cross-buy.

The main advantage of identifying exchange characteristics and firm–customer interaction variables as drivers of cross-buy behavior is that the firms can then leverage the customer data to pinpoint the customers who are likely to cross-buy. Furthermore, there is a need to quantify the benefits of cross-buy in terms of improvement in customer-based metrics. We address these issues in this study. Specifically, the objectives of our study are (1) to understand the motivation of customers to cross-buy, (2) to identify the drivers of cross-buy in non-contractual settings such as catalog retailing, and (3) to observe whether cross-buy helps to improve revenue and other customer-based outcome metrics. We start with a discussion of the conceptual background of cross-buying. In the next section, we identify the factors that may facilitate cross-buy and formulate research hypotheses relating to the drivers and consequences of cross-buy. We then propose a framework for analyzing the antecedents and consequences of cross-buy. In the subsequent section, we provide a discussion of the data and the models used to test these hypotheses. In the final section, we point out some of the limitations of this study and offer suggestions for future research.

Conceptual background

In a contractual setting, cross-buying refers to buying additional products and services from the existing service provider in addition to the ones he/she currently has (Ngobo 2004). By this definition, when a customer terminates a service, the level of cross-buy reduces compared to the previous period because cross-buying is measured as the difference in the number of services that a customer has in two consecutive periods. However, in non-contractual settings such as retail transactions, there is no equivalent to service termination and it does not seem meaningful to measure cross-buy as the difference between the number of different products purchased in two successive time periods. Hence, for studying the drivers of cross-buy in a non-contractual setting, we define cross-buy as the total number of different product categories that a customer has purchased from a firm from the time of first purchase. This definition is consistent with those used in the past studies conducted in a non-contractual setting (Reinartz and Kumar 2003; Venkatesan and Kumar 2004; Kumar and Venkatesan 2005) where cross-buying is used as an explanatory variable.

Drivers of cross-buy

One of the earliest studies on cross-buy identifies prospects for cross-selling of financial services based on the current ownership of product or services and factors such as demographic characteristics and investment objectives of the household (Kamakura et al. 1991). Recent studies have identified some of the drivers of cross-buy (Verhoef et al. 2001; Verhoef and Donkers 2005) or cross-buying intention (Ngobo 2004) in financial services. The drivers identified in these studies can be broadly classified into three: customers' attitude towards a firm and its products, socio-demographic characteristics, and marketing effort by the firm. Verhoef et al. (2001) do not find support for satisfaction or the difference in satisfaction between the focal firm and the competitors affecting cross-buy. Ngobo (2004) reported similar results from a study using two samples of service consumers. The results from this study reveal that cross-buying is only weakly or marginally associated with customer's service experience measured in terms of perceived quality, value and satisfaction. However, a contradictory finding in financial services is that overall satisfaction with a firm increases the firm's ability to cross-sell (Li et al. 2005). On the other hand, difference in payment equity (measured as perception of fairness of price) between the focal firm and its competitors, has a significant effect on cross-buying (Verhoef et al. 2001). A customer's willingness to continue the relationship and favorable evaluations of the firm's ability to provide different types of services also influence cross-buying intentions (Ngobo 2004). Besides these attitudinal measures, cross-buying is also impacted by the channel of acquisition of customers (Verhoef and Donkers 2005), the type of service (Ngobo 2004), total number of services held in the previous period (Verhoef et al. 2001), household level switching cost, demographic characteristics such as education, gender, income (Li et al. 2005), and age (Verhoef et al. 2001). Marketing instruments such as loyalty programs and the number of direct mail in the previous period are also important determinants of cross-buy (Verhoef et al. 2001).

Development of research propositions

Becker (1965) states that customers/households maximize their utility (for e.g. from shopping activity) subject to both money and time constraints. Households assess their return from shopping by analyzing total costs of shopping, which include cost of goods, inventory, transportation, opportunity, and search costs (Kumar and Karande 2000). Since households are utility maximizers, they patronize a retail store where the total costs are the least. Based on this theory, one can argue that customers' decision to buy an additional category from a retail store is also influenced by the total costs of shopping. Cross-buying offers the consumer the convenience of one-stop-shopping, which will reduce the total cost. The fact that consumers value convenience is evident in many studies over the last four decades (Cox and Rich 1964; Gehrt et al. 1996), one of which was a survey result where 90% of those surveyed stated that convenience was the motivating factor for telephone shopping (Cox and Rich 1964). While the convenience of one-stop-shopping acts as a cost reducing factor, customers' uncertainty regarding the performance of the product creates perceived risk which reduces the overall utility the customers achieve by cross-buying. Hence, perceived risk acts as a deterrent to cross-buying. The important role of perceived risk in customers' decision-making in telephone shopping (Cox and Rich 1964), and online shopping behavior (Bhatnagar et al. 2000; Cunningham et al. 2005) is well documented. Researchers have also examined how certain customer characteristics and exchange characteristics help to reduce the perceived risk at various stages of decision-making.

A shopping decision involves risk when there is uncertainty regarding the consequences (Pollatsck and Tversky 1970; Rapoport and Wallsten 1972). In a cross-buying context, the customer has no prior personal experience of buying a particular product category from the retailer. As a result, there is uncertainty regarding the performance of products in those categories which were not purchased before. When risk is perceived, customers use various risk reduction strategies. Two ways a customer reduces perceived risk include (i) reducing the uncertainty of prediction of probable consequences of his/her purchase decision, and (ii) reducing the amount at stake, which is usually resorted to only when the uncertainty with the outcome cannot be reduced (Cox and Rich 1964). One of the most common uncertainty reduction strategies employed by customers is to rely on past experience and experience of others. Another means to reduce uncertainty is to seek more information about the consequences of the purchase decision. When a customer cannot reduce the uncertainty, he/she resorts to the second strategy of risk reduction—reducing the amount at stake or in many cases not making the purchase decision. Extending this theory to the decision regarding cross-buy, one can argue that the probability of cross-buy is higher when customers can reduce the uncertainty about the consequences by either relying on the past experience or by seeking more information.

Closely related with the concept of perceived risk is trust. Trust exists when one party has confidence in an exchange partner's reliability and integrity (Morgan and Hunt 1994). Another definition by Moorman et al. (1993) includes reliability and confidence as the key elements of trust. These and many other definitions[1] of trust include, either explicitly or implicitly, a risk component expressed in terms like confidence (Morgan and Hunt 1994), fear (Bradach and Eccles 1989), predictability (Gabarro 1978), and reliability (Moorman et al. 1993). The concept of trust therefore is interwoven with the concept of risk. Trust is also viewed as an attribute of risk-taking (Mayer et al. 1995). A sense of trust encourages risk-taking by trustors (Das and Teng 2004). Researchers have highlighted the critical role trust plays in reducing the perceived risk. In a framework of trust and risk, Das and Teng (2004) illustrate that trust antecedents lead to subjective trust, which is considered as a mirror image[2] of perceived risk. The subjective trust then leads to behavioral trust or risk taking. Furthermore, there are two independent sources of subjective trust. One refers to partner's *ability* to perform according to agreements (competence trust) and the other refers to his *intentions* to do so (goodwill trust) (Nooteboom 1996; Das and Teng 2004). Similarly, perceived risk has two dimensions—relational risk and performance risk. Relational risk is the probability that the partners may not be fully committed to the relationship. Performance risk on the contrary, is the probability that the partner may not be able to perform given his full commitment. Further goodwill trust is related inversely with the relational risk and competence trust is inversely related to performance risk (Das and Teng 2004). Thus, an increase in the components of trust reduces the perceived risk and facilitates risk-taking behavior, which in a cross-buying context is buying from an additional product category.

Following from the existing theory of perceived risk and trust, we develop hypotheses regarding the drivers of cross-buy. In this research, we study exchange characteristics (Reinartz and Kumar 2003; Venkatesan and Kumar 2004), marketing effort by the firm (Reinartz et al. 2005; Venkatesan and Kumar 2004), customer characteristics, and product characteristics as drivers of cross-buy. The relationships of these factors with cross-buy, as postulated in Table 1, are based on their influence either to reduce/increase the perceived risk regarding the consequences of a cross-buy decision or to increase/decrease subjective trust.

We use customer characteristics such as household income, age of the head of the household as control variables. Indicator variables for categories from which a customer has made his/her first purchase are also used as control variables in our study to understand whether category of first purchase is a significant predictor of cross-buy.

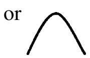
The impact of cross-buy on customer-based metrics

We analyze the impact of cross-buy by comparing outcome variables such as increase in revenue, contribution margin and number of orders per month. When a customer buys multiple product categories, there is a higher likelihood of him/her purchasing more product categories in each purchase occasion. The customer has more product categories and therefore more products to choose from in any purchase occasion—that is the customer shops at the store for wider range of products. Based on the above facts, we develop the hypotheses regarding the consequences of cross-buy, which along with supportive arguments

[1] For various definitions of trust please refer Das and Teng (2004).

[2] The subjective trust is the assessed probability of having desirable action; where as perceived risk is the assessed probability of not having desirable results. Thus a perception of low trust implies a perception of high risk.

Table 1
Hypotheses regarding drivers and consequences of cross-buy

Variable	Hypothesis	Expected direction	Reasoning	Supporting literature
Drivers of cross-buy				
Exchange characteristics				
Average inter-purchase time	Hypothesis 1: The average inter-purchase time exhibits an inverted U-shaped relationship with cross-buy		Increased goodwill and competence trust resulting from more frequent interactions. However, large numbers of customers who purchase at very short intervals leave the firm at early stage of the relationship	Kumar and Venkatesan (2005), Garbarino and Johnson (1999) and Becerra and Gupta (2003)
Product returns	Hypothesis 2: There exists an inverted U-shaped relationship between product returns and cross-buy		Positive experience with firm's return process increases goodwill trust. However, too many returns reduce the competence trust and increases perceived risk	Cox and Rich (1964), Venkatesan and Kumar (2004)
Focused buying	Hypothesis 3: The higher the level of focused buying, the higher the cross-buy	+	Familiarity with products in a category coupled with consistent positive experience builds 'company credibility' and 'competence trust' in the firm's offerings. This lowers the perceived risk of buying from other categories	Keller and Aaker (1992) and Reinartz and Kumar (2003)
Marketing effort				
Direct mailings	Hypothesis 4: Cross-buy increases with increase in the number of direct mailings up to a threshold, beyond which there is saturation or a decline in the incremental effect	 or 	Higher number of mailings improves trust (due to familiarity) and reduces perceived risk (owing to more information). But, the value of incremental information gathered or familiarity acquired decreases beyond a threshold. It is also possible that customers may be annoyed by too many direct mailings, thereby negatively impacting the effect of mailings	Morgan and Hunt (1994), Reinartz and Kumar (2003), Bolton et al. (2004) and Verhoef et al. (2001)
Cross promotions	Hypothesis 5: The mailing of cross-category catalog has a positive relationship with cross-buy	+	Ability to gather more information about products in a new category reduces the perceived risk of buying from the new category	Senecal and Nante (2004)
Consequences of cross-buy				
Revenue per order	H6: The higher the cross-buy, the higher the revenue per order per customer	+	Increase in the choice of product categories (higher cross-buy) and products helps customer to shop for a wider range of products in a purchase occasion	Venkatesan and Kumar (2004)
Contribution margin per order	Hypothesis 7: The higher the cross-buy, the higher the contribution margin per order per customer	+	Customers may buy high-end products (with higher contribution margin) because of improved trust	
Number of orders in a given time period	Hypothesis 8: The higher the cross-buy, the higher the number of orders in a given time period per customer	+	With higher number of product categories to choose from (or higher cross-buy), the likelihood of placing an order increases	

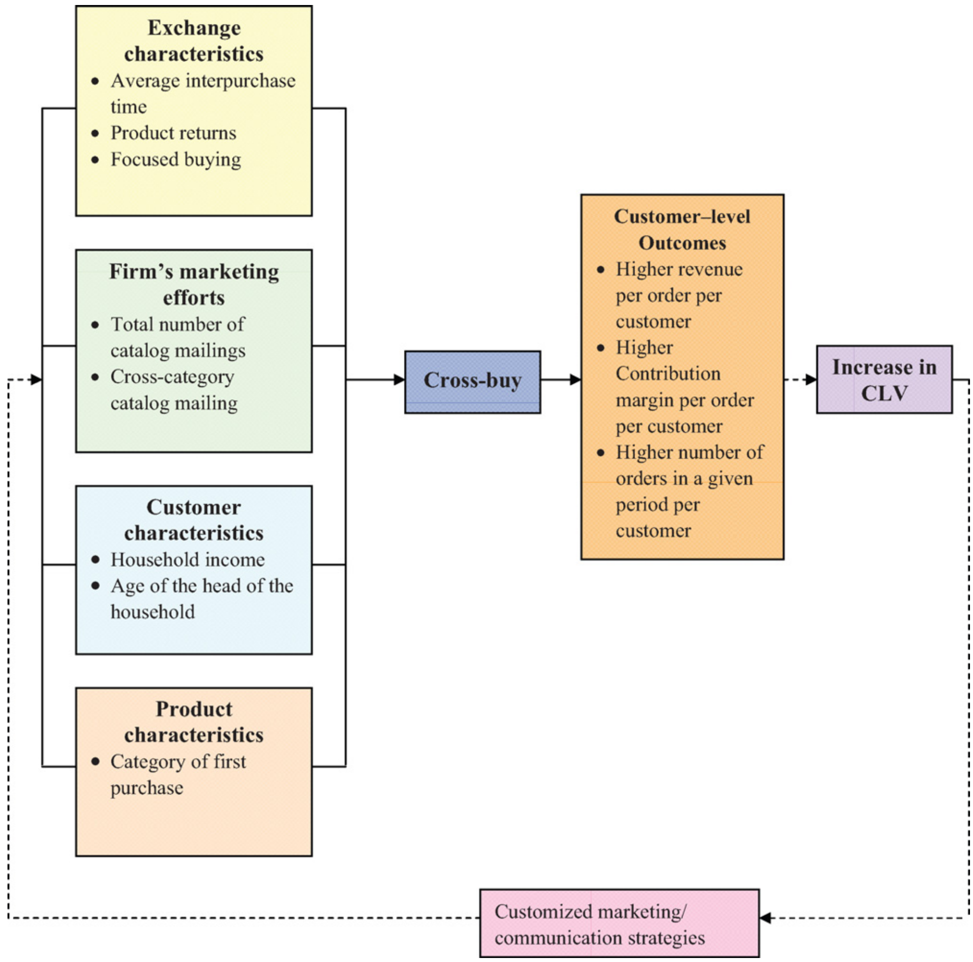


Fig. 1. A framework for analyzing the drivers of cross-buy.

are given in Table 1. The drivers of cross-buy and the impact of cross-buy on customer-based outcome metrics are summarized in the framework given in Fig. 1.

Research methodology

Research context

As discussed in 'Introduction' section, the purpose of this study is to identify the drivers of cross-buy in a non-contractual setting. Specifically, we want to identify the variables, obtainable from the firm's database, which act as drivers of cross-buy so that they can be used for the selection of customers for directing the cross-selling efforts. We use catalog retailing as an example of non-contractual setting for the purpose of our study.

Data

Transaction data and firm–customer interaction data from a large catalog retailer are used for this study. The customer purchase history is available for a period starting from 1997 to 2004. The firm sells products in seven major product categories that make this database rich for studying cross-buying behavior. An average customer has purchased 2.9 product categories and the average number of purchases per customer is 7.8 per year for the whole time period. Apart from transaction data, we also have information on the firm's direct mailing efforts and the cross-category promotions for this period. The firm usually sends a customer catalogs pertaining to product categories purchased previously as well as those featuring other categories. On an average the firm mails 15.7 catalogs per year per customer. Customer demographic data, also available in the same database serve as control variables.

We selected a cohort of customers who made their first purchase in 1997. We then randomly chose two samples consisting of about 1500 observations. One sample, (i.e. calibration sample) is used for model building purposes, and the other for out-of sample validation of our model.

Operationalization of variables

We use transactions until December 2002 to compute current and cumulative variables used in the study. For each customer, we first identify the purchase occasion where the customer has purchased from an additional product category. The current (i.e. from the last instance of cross-buy) and cumulative (i.e. from the first purchase occasion) variables are then computed using transactions until the previous purchase occasion

Table 2
Operationalization of variables and descriptive statistics

Variable	Operationalization of variables	Mean	*SD*
Cross-buying	Number of product categories purchased during January 1997-current purchase occasion	2.62	1.36
Exchange characteristics			
Average interpurchase time (AIT)	Average time (in months) between purchases during Jan 1997 until the previous purchase occasion	5.60	6.47
Ratio of product returns	Ratio of dollar amount of product returns to the total amount of purchases during Jan 1997-previous purchase occasion.	0.15	0.29
Focused buying_Men's	No. of products purchased from a particular Dept during Jan 1997-previous purchase occasion	1.70	4.24
Focused buying_Women's		1.82	5.69
Focused buying_Kids'		0.80	3.19
Focused buying_Outdoor		0.29	0.95
Focused buying_Luggage		0.61	1.77
Focused buying_Home		0.40	1.48
Average Past Revenue	Average quarterly revenue during Jan 1997-previous purchase occasion.	47.2	103.7
Marketing effort			
Direct mailings	Average number of catalogs sent per quarter during January 1997-previous purchase occasion	2.79	2.90
Cross-promotion	An indicator variable for sending a cross-category catalog from first purchase until previous purchase. (1 for sending; 0 otherwise)	0.41	0.49
Product characteristics			
First Purchase_Men's	An indicator variable showing whether first purchase was from a particular department (1 for purchase and 0 otherwise)	0.44	0.49
First Purchase_Women's		0.34	0.47
First Purchase_Kids		0.10	0.29
First Purchase_Outdoor		0.08	0.27
First Purchase_Luggage		0.17	0.38
First Purchase_Home		0.12	0.32
Customer characteristics			
Household income	Household income in '000	107.1	38.5
Age	Age of the head of the household	44.1	12.1

(i.e. $t-1$) with respect to the time of cross-buy. The lagged values of the independent variables are considered so as to find their causal relationship with the dependent variable. The number of dependent and independent variables will be different for each customer depending upon the number of product categories the customer has purchased during January 1997 to December 2002. For instance, a customer who purchased 6 product categories will have 6 values for cross-buy (dependent variable) and 6 sets of independent variables corresponding to each value of cross-buy.

We provide the operationalization of the variables in Table 2 along with their means and standard deviations.

Dependent variable

Cross-buy: The dependent variable, cross-buy is measured as the total number of product categories purchased from January 1997 until (including) the current purchase occasion. This will take the values 1, 2, . . ., 7.

Independent variables

Average interpurchase time: Average interpurchase time is computed as average time in months between orders for all orders during the period January 1997 until the previous purchase occasion.

Product returns: Product returns are always linked to prior purchases and hence a meaningful measure of product returns will be a relative measure of product returns to prior purchases. We therefore use ratio of returns instead of absolute number or amount of product returns. The ratio of returns is calculated as the ratio of the dollar amount of products returned during January 1997—until the previous purchase occasion to the total dollar amount of orders placed in the same period.

Focused buying: The focused buying (or the depth of purchase) in a category is measured as the total number of orders placed in that category between January 1997 and the previous purchase occasion.

Direct mailings: We use the average number of catalogs sent to a customer in a quarter as a measure of direct mailings[3].

[3] This is to avoid the possibility of serial correlation within each customer. We thank the anonymous reviewer for pointing out the possibility of serial correlation when using cumulative independent variables.

Table 3
Correlation matrix of the drivers of cross-buying

	Cross-buy	Average interpurchase time	Ratio of return amount	Focused buying Men's department	Focused buying Women's department	Focused buying Kids' department	Focused buying Outdoor department	Focused buying Luggage department	Focused buying Home department	Average Past Revenue	Direct mailings	Indicator_Cross promotions	Household income	Age of the head of household
Cross-buy	1.0													
Average Interpurchase Time	0.25	1.0												
Ratio of return amount	0.24	0.17	1.0											
Focused buying_Men's	0.41	0.02	0.09	1.0										
Focused buying_Women's	0.41	−0.04	0.07	0.45	1.0									
Focused buying Kids'	0.33	−0.02	0.06	0.12	0.10	1.0								
Focused buying_Outdoor	0.36	0.03	0.02	0.19	0.25	0.08	1.0							
Focused buying_Luggage	0.40	0.04	0.02	0.15	0.15	0.24	0.11	1.0						
Focused buying_Home	0.34	0.04	−0.02	0.22	0.18	0.05	0.12	0.14	1.0					
Average Past Revenue	0.26	−0.14	−0.02	0.30	0.33	0.09	0.20	0.08	0.12	1.0				
Average number of direct mails per quarter	0.71	0.21	0.33	0.45	0.44	0.34	0.25	0.35	0.30	0.19	1.0			
Indicator_Cross promotions	0.60	0.58	0.28	0.27	0.23	0.20	0.22	0.27	0.21	−0.06	0.51	1.0		
Household income	0.04	0.06	0.02	0.01	0.01	0.01	0.07	0.06	0.02	−0.01	0.05	0.07	1.0	
Age of the head of household	0.03	0.05	0.08	0.08	−0.02	−0.01	0.04	0.01	0.05	−0.02	0.03	0.11	−0.14	1.0

Cross-promotions: A catalog that predominantly features categories that have not been purchased before is considered as a cross-category catalog. Cross-promotion is measured as an indicator variable, which takes a value 0 if no cross-category catalog was sent during the period between first purchase and present cross-buy, and a value 1 otherwise.

Covariates: A number of variables such as household income, age of the head of the household, and category of first purchase are used as covariates.

The correlations among the variables are presented in the correlation matrix given in Table 3.

An examination of variance inflation factors of variables when used as independent variables in a multiple regression reveal that there is no multicollinearity.

Statistical model

Cross-buy is operationalized as the number of product categories purchased and it takes the values 1,2,3, . . ., 7 in our data. This is similar to the popular examples of count data such as the number of patents issued to a firm and the number of accidents in a country. We can also observe the explanatory variables between every change in the dependent variable so that we can identify the impact of both current and cumulative variables on the dependent variable. Because the dependent variable is a count variable, either Poisson regression or a negative binomial regression (NBD) model are possible statistical models for this study. However, Poisson or NBD do not address some of the key issues we face in modeling cross-buy as a function of the above-mentioned independent variables.

One important concern is the possibility of reverse causality. We hypothesize that the average interpurchase time (or the purchase frequency) is an important determinant of cross-buy because of its influence on the trust and the perceived risk of the customer. However, one can argue that once a customer start buying from more product categories, his/her purchase frequency may increase (or the average interpurchase time may decrease) because of the increase in the breadth of choices. In other words, cross-buy influences future interpurchase time. Past research (Reinartz and Kumar 2003) has shown that cross-buy is a driver of CLV, which is computed using purchase frequency, number and cost of marketing communications, and contribution margin in the future time periods. The positive impact of cross-buy on CLV suggests that cross-buy in current time period is likely to affect the average inter purchase time (or purchase frequency) in the future time period. Another issue that needs consideration is regarding endogeneity. A company's decision to mail a catalog to a customer may be based on the revenue contribution (Monetary value) from that customer in the past and possibly on the number of orders placed (Frequency) by the customer. Hence, the number of direct mailings may not be an exogenous variable. In order to address these possible issues we can estimate the parameters in a system of equations framework. The three equations in the system can be written as follows:

$$\begin{aligned} Crossbuy_t = {} & \beta_0 + \beta_1 * AIT_{t-1} + \beta_2 * AIT^2_{t-1} \\ & + \beta_3 * Product\ returns_{t-1} \\ & + \beta_4 * Product\ returns^2_{t-1} \\ & + \beta_5 * Direct\ mailings_{t-1} \\ & + \beta_6 * Direct\ mailings^2_{t-1} \\ & + \ldots + \beta_K * Household\ income + \varepsilon_{1t} \end{aligned} \tag{1}$$

$$\begin{aligned} AIT_t = {} & \alpha_0 + \alpha_1 * Crossbuy_{t-1} + \alpha_2 * Duration_{t-1} \\ & + \alpha_3 * Average\ revenue_{t-1} + \alpha_4 * Income + \varepsilon_{2t} \end{aligned} \tag{2}$$

$$\begin{aligned} Direct\ Mailing\ rate_t = {} & \gamma_0 + \gamma_1 * Number\ of\ orders_{t-1} \\ & + \gamma_2 * Average\ revenue_{t-1} \\ & + \gamma_3 * Income + \varepsilon_{3t}. \end{aligned} \tag{3}$$

Since the determination of the dependent variables in the system of equations given above are interdependent, the errors, $\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}$ may be correlated. In order to estimate the parameters consistently, we need to take into account the correlation among the errors[4]. The seemingly unrelated regression (SUR) model can be used to estimate the parameters in a system of equations where the errors are correlated. The SUR model is as follows:

$$y_i = X_i\beta_i + \varepsilon_i, \quad i = 1, 2, \ldots, M \tag{4}$$

where $\varepsilon = [\varepsilon_1' \quad \varepsilon_2' \quad \varepsilon_M']$ are the correlated errors.

There are M equations in the system (in our case $M = 3$) each having k_M regressors. The Eq. (4) can be written using the matrix notation as given below:

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & 0 & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ . \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ \varepsilon_M \end{bmatrix} = X\beta + \varepsilon \tag{5}$$

where X_M is the set of k_M regressors in Mth equation. The Eq. (5) is then similar to multivariate regression equation and can be estimated using generalized least squares (GLS) if the variance–covariance matrix of errors is known. In most cases, such as the one we are dealing with, the variance–covariance matrix (Ω) is unknown. Then we can use Feasible GLS (FGLS), which first estimates the elements of Ω using residuals from the OLS regression of each of the M equations. The variance–covariance matrix thus obtained is then used to estimate the parameters of the system of equations.

While the estimation of the parameters using SUR model addresses the problems of reverse causality and endogeneity, another issue that needs to be addressed is the observed and unobserved heterogeneity among customers. We account for the observed heterogeneity by using the demographic or customer characteristic variables as control variables in the equation. We incorporate unobserved heterogeneity by using a random coefficient model. This model allows for the variation in the coefficients across customers. Such parameter heterogeneity across customers or households can be modeled as stochastic variation. This means that instead of a constant β for all households as shown in (5), a household-specific β_h is assumed for each household. We can then write

$$Y_h = X_h\beta_h + \varepsilon_h, \quad h = 1, 2, \ldots, H \tag{6}$$

where

$$\beta_h = \beta + u_h. \tag{7}$$

Thus, each β_h is assumed to be a random draw from a distribution with mean β and variance Σ. We specified a normal distribution for β_h because we did not want to restrict the sign of any coefficient.

$$\text{Thus,} \qquad \beta_h \sim N(\beta, \Sigma). \tag{8}$$

The parameters can be estimated using maximum simulated likelihood (MSL) method (Greene and William 2002). The density of y_h when parameter vector is β_h is f $(y_h|x_h, \beta_h)$. If the parameters are assumed to have a density function, $g(\beta)$ then the unconditional density for y_h is obtained by integrating over β_h.

$$f(y_h|X_h, \beta, \Sigma) = \int_{\beta_h} f(y_h|X_h, \beta_h) g(\beta_h|\beta, \Sigma) \mathrm{d}\beta_h. \tag{9}$$

Then, the true log-likelihood would be

$$\ln L = \sum_{h=1}^{H} \ln \left\{ \int_{\beta_h} f(y_h|X_h, \beta + u_h) g(u_h|\Sigma) \mathrm{d}\beta_h \right\}. \tag{10}$$

However, there is no close form for the above integral and we cannot compute it directly. One way to compute the above log-likelihood function is approximation through simulation. The simulation is done as follows: (1) Draw a value of β_h from $f(\beta_h|\beta, \Sigma)$, and label it β^r with $r = 1$ referring to the first draw. (2) Calculate the log-likelihood of the SUR model, $LL(\beta^r)$ using β^r. (3) Repeat steps 1 and 2 many times and compute the simulated log-likelihood (SLL) by taking the average of the values of log-likelihood in each β^r draws.

$$\mathrm{SLL} = \frac{1}{R}\sum_{r=1}^{R} \mathrm{LL}(\beta^r). \tag{11}$$

For a sample of T observations, the log-likelihood of the SUR model given in (5) can be written as:

$$LL(\beta^r) = -\frac{MT}{2}\ln(2\pi) - \frac{T}{2}\ln|\Omega| - \frac{1}{2}\sum_{t=1}^{T} \varepsilon_t' \Omega^{-1} \varepsilon_t \tag{12}$$

where M is the number of equations in the system and Ω is the variance–covariance matrix of the errors of the M equations.

[4] Bolton et al. (2004) point out the importance of considering the simultaneous relationships among different purchase behaviors when they proposed the CUSAMS framework for customer asset management.

The maximum simulated likelihood estimator (MSLE) is the values of β and Σ that maximize the simulated log-likelihood (SLL). The results from the estimation include the mean value of the parameter estimates and the variance of the distribution of the parameters. Depending on the statistical significance of the parameter estimates, we can test the hypothesized relationship and establish the drivers of cross-buy.

Impact of cross-buy

To study the impact of cross-buy, we compared the values of customer-based metrics before and after an increase in the level of cross-buy (i.e. after the customer started purchasing from an additional category). We computed the mean value of the customer-metrics such as revenue and contribution margin per order and orders per month. We then compared the group means to see whether any one group is significantly different from any of the other groups using MANOVA (Kumar and Venkatesan 2005).

Results

The mean and standard deviation of parameters in the cross-buy equation estimated using random coefficient SUR model are given in Table 4.

We allowed random coefficients for eight main variables – average interpurchase time (AIT), square of AIT, ratio of returns and its square, average quarterly revenue, number of catalogs and its square, and cross-promotion indicator – and intercept. Even though the model allows variation of parameter estimates across households, the results show that the extent of variation as captured by the standard deviation of the parameter distribution is very low. Also, the log-likelihood and the parameter estimates of this model are very similar to those obtained for a model without incorporating heterogeneity. We have also compared the model results with those from latent class estimation. A two segment latent class model results show the sizes of the segment masses as 0.9999 and 0.0001. The parameter estimates in the larger segment are similar to those obtained using random coefficient model. These results demonstrate that the heterogeneity is accounted for by the observed variables in the equation and there is no unobserved heterogeneity[5]. The parameter estimates and the *p*-values show that the variables in the model are significant and in the expected direction as discussed below.

Exchange characteristics

Average interpurchase time (AIT) was hypothesized to show an inverted U-shaped relationship with cross-buy. In order to capture such relationship, we used the square of AIT along with AIT in the model. The coefficient of AIT is positive (0.0375) and significant at $\alpha < 1\%$, whereas the coefficient of the square of AIT is negative (−0.0014) and significant at $\alpha < 1\%$. The inverted U-shaped relationship of AIT indicates that as the interpurchase times increases, the cross-buy increases initially but decreases after a threshold level of AIT. These findings support Hypothesis 1. The coefficient of the ratio of product returns is positive (1.048) and significant at 1% significance level and that of the square of the ratio of product returns is negative (−0.8962) and significant at $\alpha < 1\%$. These results indicate that even though cross-buy increases with increase in the ratio of product returns relative to the purchase amount, beyond a certain threshold, the ratio of product returns has a negative impact on cross-buy. This finding is in support of Hypothesis 2, which implies an inverted U-shaped relationship for ratio of product returns with cross-buy. The results are also in support of the hypothesized relationship (Hypothesis 3) between focused buying and cross-buy. The parameter estimates for the focused buying (in different product categories) variables are all positive and significant at <1% level as given in Table 4.

Marketing efforts

The coefficient of the number of catalogs sent per quarter is positive (0.2218) and significant ($\alpha < 1\%$) and that of the square of the number of catalogs sent is

[5] We ran several combinations of variables in our model, and the unobserved heterogeneity was significant for estimations with a smaller set of explanatory variables, but our estimates indicate that the effect of unobserved heterogeneity seems to be diminished as we added the full set of explanatory variables used in our estimation.

Table 4
The mean and standard deviation of parameter estimates in the cross-buy equation estimated using Random Coefficient SUR Model

Variables	Mean parameter estimates
Intercept	0.2605*
Exchange characteristics	
Average interpurchase time (AIT)	0.0375***
Square of AIT	−0.0014***
Ratio of product returns	1.048***
Square of the ratio of product returns	−0.8962***
Focused buying in Men's department	0.0171***
Focused buying in Women's department	0.0327***
Focused buying in Kids' department	0.0503***
Focused buying in Outdoor department	0.3477***
Focused buying in Luggage department	0.0781***
Focused buying in Home department	0.0650***
Average quarterly revenue	0.0015***
Firm's marketing effort	
Number of catalogs sent per quarter	0.2218***
Square of the number of catalogs sent per quarter	−0.0131***
Indicator_Cross promotion	0.7043***
Product characteristics	
First Purchase_Men's Dept	0.1750**
First Purchase_Women's Dept	0.1555**
First Purchase_Kids' Dept	0.2392***
First Purchase_Outdoor Dept	*ns*
First Purchase_Luggage Dept	*ns*
First Purchase_Home Dept	0.4497***
Customer characteristics	
Age of the head of the household	0.0138**
Square of Age	−0.0002***
Household income (in '000)	0.0033*
Square of income	−0.00002**

Heterogeneity parameters	*SD*[a]
Intercept	<0.0001
Average interpurchase time (AIT)	<0.0001
Square of AIT	<0.0001
Ratio of product returns	<0.0001
Square of the ratio of product returns	<0.0001
Average quarterly revenue	0.0006
Number of catalogs sent per quarter	<0.0001
Square of the number of catalogs sent per quarter	0.0002
Indicator_Cross promotion	<0.0001
Model fit	
−(Log-likelihood)	13,293
Bayesian information criterion	26,950
Akaike information criterion	26,674

*Significant at $\alpha < 10\%$, **Significant at $\alpha < 5\%$, ***Significant at $\alpha < 1\%$.
[a] This is the standard deviation of the heterogeneity parameter distribution (multivariate normal with diagonal covariance matrix).

Table 5
Out-of-sample hit rate of the SUR Model

	Purchased only one product category	Purchased two product categories	Purchased three product categories	Purchased four or more product categories	Total
Expected to purchase only one product category	198[a]	9	1	0	208
Expected to purchase two product categories	21	144[a]	54	8	227
Expected to purchase three product categories	2	46	102[a]	36	186
Expected to purchase four or more product categories	0	7	61	153[a]	221
Total	221	212	218	197	842

[a] The prediction accuracy is significantly different from the prediction based on chance. Overall, the model classified 71% of the cases correctly.

negative (−0.0131) and significant ($\alpha < 1\%$). These findings support Hypothesis 4, which postulates that cross-buy increases with increase in the number of direct mailings up to a threshold, beyond which there is saturation or a decline in the incremental effect. The firm's cross-selling effort, measured as whether any cross-category catalog was mailed to the customer, is significant (at <1% level). The parameter estimate of cross-promotion is positive (0.7043). These results strongly support Hypothesis 5 that cross promotions has a positive impact on cross-buy.

Customer characteristics

We use household income and age of the head of the household as customer characteristic variables. The results illustrate that both household income and age of the head of the household are significant predictors of cross-buy. The inverted U-shaped relationship that these variables have with cross-buy indicates that the intermediate values of age and income are associated with higher cross-buy.

Product characteristics

We use indicator variables representing the category from which customers have made their first purchase. The results show that cross-buy depends on the category of first purchase. Specifically, customers who made their first purchase from Home, Kids', Men's and Women's categories are more likely to cross-buy compared to those customers who made their first purchase from Outdoor and Luggage categories.

Model fit

The random coefficient seemingly unrelated regression (SUR) model applied to the calibration sample shows a very good fit with the data. The log-likelihood of the full model is 13293 compared to 16506 for the intercept only model[6]. Thus, the likelihood ratio is 6426 and this value with 25 *df* is statistically significant at $\alpha < 1\%$. Also, the in-sample hit-rate is 73%. We also tested the out-of sample predictive accuracy of the model by applying the model coefficients to score the validation sample. The resulting classification table containing the number of customers correctly classified under different levels of cross-buy is given in Table 5.

We applied the *t*-test suggested by Frank et al. (1965) to see whether our model provides better prediction compared to that based on chance. Kumar and Venkatesan (2005) used a similar *t*-test in an ordered logit case. The *t* tests indicate that the accuracy of prediction for all levels of cross-buy is significantly better than that for the prediction based on chance. Overall, the model classified 71% of the cases correctly.

Impact of cross-buy on customer-based metrics

The results of MANOVA are given in Fig. 2.

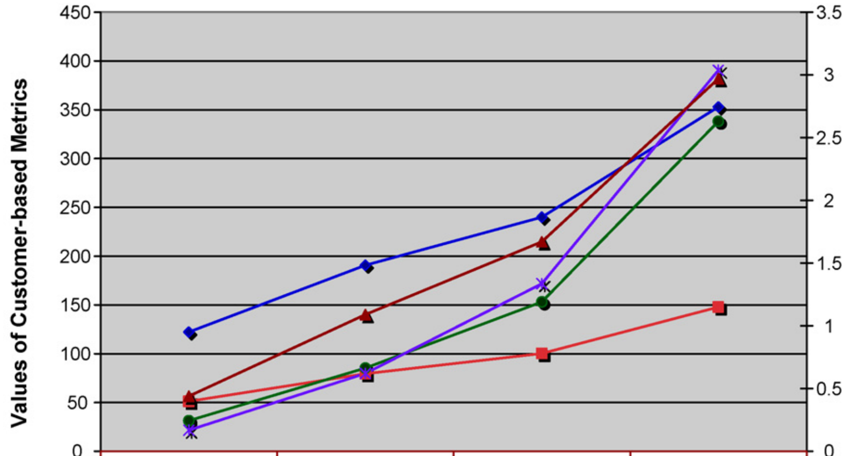
The model significance shows that customer-based metrics are significantly different for different levels of cross-buy. For example, the average revenues per order per customer are 122.2, 190.7, 239.9, and 352.9 for customers who purchased one, two, three, and four or more categories respectively. The average revenue per order per customer for any particular level of cross-buy is significantly higher than that for the previous level. Similar differences across four levels of cross-buy can be seen with respect to average contribution margin per order, and average orders per month. The average orders per month for customers who purchased from four or more product categories (2.97) is significantly higher than that of customers who purchased three categories (1.67) which in turn is significantly higher than the orders per month by customers who purchased two categories (1.09). Compared to the average orders placed per month by customers who purchased only one category (0.44), that of customers who purchased more than one category are significantly higher. The increase in revenue and contribution margin per order, and orders per month has contributed to an increase in revenue and contribution margin per month, which are significantly different across different levels of cross-buy.

Discussion and managerial implications

The results of our study have several implications for a retail manager. The results show that average interpurchase time has an inverted U-shaped relationship with cross-buy. This means that customers who purchase at intermediate duration are more likely to purchase from additional categories. One reason for this is that a large number of customers who purchase at very short intervals are those who purchase fewer times from the company and then never return. They are like strangers/butterflies (Reinartz and Kumar 2002), whose relationship durations are very short. On the other extreme are customers who make only occasional purchases (i.e. their AIT is very high) and therefore the number of interactions with the firm is too low to develop trust with the firm. Whereas, customers who purchase at intermediate intervals remain with the firm for a longer duration (Reinartz and Kumar 2003) and make frequent purchases, resulting in less perceived risk and higher cross-buy. Previous research has also found support for an inverted U-shaped relationship of the average interpurchase time[7] with profitable lifetime duration (Reinartz and Kumar 2003), customer lifetime value (Venkatesan and

[6] The cross-buy equation has only intercept while other two equations have the same variables as in the full model.

[7] In some studies purchase frequency is used instead of average interpurchase time. In such cases the relationship will be in the opposite direction.



	One	Two	Three	Four or more
Revenue/Order	122.2	190.7	239.9	352.9
CM/Order	51.2	79.6	100.3	147.9
Revenue/Month	31.4	85.3	153.1	338.2
CM/Month	21.6	79.9	171.8	390.6
Orders/Month	0.44	1.09	1.67	2.97

Number of Product Categories Purchased

Fig. 2. The impact of cross-buy on customer-based metrics.

Kumar 2004), and multichannel shopping behavior (Kumar and Venkatesan 2005). Two main implications of these findings for the managers are (i) target customers who purchase at intermediate time intervals for cross-selling, and (ii) devise strategies to make butterflies remain longer with the firm so that with improved trust and less risk (owing to more interactions with the firm), they can be potential targets for cross-sell/up-sell.

Another important finding is the impact of product returns on cross-buying. The results show that the ratio of product returns exhibits an inverted U-shaped relationship with cross-buy. The negative impact of ratio of product returns beyond the threshold level may be because increase in the amount of product returns relative to the increase in the purchase amount can decrease customer's competence trust with the firm. There could be two explanations for higher ratio of returns. First, there may be a mismatch between the customer's expectation and the firm's offering. If a customer has to return a large proportion of products he/she purchased, he/she would start to question the ability of the firm to offer products that meet his/her needs. Second, a higher ratio of returns may be the manifestation of possible negative return behavior. Customers may be misusing the return system. Recent industry examples such as Best Buy classifying certain customers as 'demons' (Selden and Colvin in press), point toward the fact that some customers do exhibit such negative return behaviors (Cha 2005). In both of these cases, the customer is not a potential target for cross-sell effort. Whereas, customers are unlikely to extend the relationship with the firm if there is a perceived mismatch between customer's expectations and firm's offerings, it may not be profitable for firms to cross-sell to customers who exhibit negative return behavior. The results regarding the impact of product return on cross-buy have important implications for managers. Based on the findings, product returns are not necessarily bad. Firms should consider any instance of product return as an opportunity to interact with a customer and satisfy him/her. It is very important to manage the return process efficiently and effectively so that the customer is satisfied and the improved trust in the firm and its offering will attract him/her to purchase more product categories. However, firms need to study cases of high ratio of returns on an individual basis to see whether it is due to any negative return behaviors, and discourage such behaviors.

The present study provides strong support for the effect of marketing efforts of the firm on the cross-buying behavior of customers. The mailing effort (i.e. the number of catalogs sent per quarter) has a significant impact on cross-buy. Cross-buy increases initially with the increase in the number of direct mailings, but beyond a certain threshold, the effect of direct mailings on cross-buy is negative. Recent studies also present evidence for the positive impact of mailing efforts on cross-buy (Verhoef et al. 2001). The inverted U-shaped relationship of the number of catalogs sent per quarter indicates that firms need to optimize their mailing efforts in order to maximize cross-buy. Some recent studies (Gonul and Shi 1998; Gonul and Hofstede 2006; Elsner et al. 2003) have also emphasized the need to optimize the mailing efforts.

The impact of cross-selling efforts on cross-buy also holds significance for retailers. The cross-selling effort, measured as whether any cross-category catalogs were mailed from the time of first purchase, has a highly significant and positive impact on cross-buy. The increased efforts by the fast moving consumer goods (FMCG) manufacturers to cross-sell their master brands are consistent with this finding. This finding reveals an opportunity for a catalog retailer to use catalogs as a cross-selling tool. The current models for optimizing catalog mailings address the question of how many customers should receive catalog and when. In order to use catalogs as an effective cross-selling tool, firms need to modify their current optimization models to address the question of what type of catalogs should be sent to a specific customer. This calls for developing category-specific catalogs as well as new optimization models for multi-category catalog mailings so as to maximize profits from cross-category promotions. Recent trends in the industry show that many catalog retailers are mailing category-specific catalogs to customers. The Home Depot, Staples, and apparel retailers like L.L. Bean are some examples. Staples, for instance, has Office products catalog, Furniture catalog, Mail and Ship catalog and Holiday Card catalog. The next logical step for these firms is to use these catalogs as an effective cross-selling tool with the help of multi-category catalog mailing models.

The results of MANOVA show that an increase in the number of product categories purchased can positively impact the performance of the firm. The revenue and contribution margin per order per customer and the number of orders in a given time period increase significantly ($\alpha = 5\%$) with each level of cross-buy. The increase in sales due to cross-selling is also reported in the industry. According to a study[8] in 2004, Unilever reported an increase in dollar share and sales of Dove personal wash products by cross-selling the Dove master brand. The results of our study and the industry example cited above reiterate the need for identifying the potential targets for cross-sell effort and enhancing the drivers of cross-buy.

Conclusion

Firms are increasingly trying to leverage their brand value to maximize revenues and profits. One of the ways firms achieve this is by cross promoting different categories under a master brand. Many firms are seeing success in their cross-selling efforts. However, the impact of cross-selling can be greatly improved if firms identify and target the right customers for cross-selling. This can be achieved by first identifying the drivers of cross-buy, which can then be used for classifying the customers. In this study, we identified exchange characteristics such as average interpurchase time, ratio of product returns, and focused buying as important drivers of cross-buy. We have also identified customer characteristic such as age of the head of the household and household income and product characteristics such as category of first purchase as other important variables. The impact of marketing efforts of the firm on cross-buy has also formed part of our analysis. The information on exchange characteristics and customer characteristics are usually available with the firm. Understanding the relationship of these variables with cross-buy will help firms to select customers with a higher likelihood of cross-buy. Knowledge of the impact of cross-selling efforts will aid firms in contacting the selected customers with the right amount of cross promotions. Thus, identification of the drivers of cross-buy gives firms an important tool to maximize the effectiveness of cross promotion of product categories or brands.

We identified behavioral variables and firm's marketing effort as the key drivers of cross-buy. However, it is possible that certain attitudinal variables like customer's affinity towards the firm/brand, and perceived quality and value of the offering play important roles in predicting cross-buy. Exclusion of attitudinal variables in our study may be considered a limitation. Also, a firm's marketing efforts in terms of bundling two or more products was also not included in the model due to lack of availability of appropriate data.

Finally, the firm's effort is dependent on the Customer Lifetime Value, which is influenced by cross-buy. Cross-buy, on the other hand, is driven by the firm's marketing effort. This can cause issues such as simultaneity, which may be addressed in future research.

Acknowledgments

The authors thank the major retailer for providing the data for this study. The authors also thank the reviewers, the Area Editor and the Editors for their comments on earlier versions of the manuscript.

References

Becerra, Manuel and Anil K. Gupta (2003). "Perceived trustworthiness within the organization: The Moderating Impact of Communication Frequency on Trustor and Trustee Effects," *Organization Science,* 14 (1) 32–44.

Becker, Gary S. (1965). "A Theory of the Allocation of Time," *The Economic Journal,* 493–517.

Bhatnagar, Amit, Misra Sanjog and H. Raghav Rao (2000). "On Risk, Convenience, and Internet Shopping Behavior," *Communications of the ACM,* 43 (11) 98–105.

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

Bolton, Ruth. N., Katherine N. Lemon and Peter C. Verhoef (2004). "The Theoretical Underpinnings of Customer Asset Management: A Framework and Propositions for Future Research," *Journal of the Academy of Marketing Science,* 32 271–292.

Bradach, J.L. and R.G. Eccles (1989). "Price, Authority, and Trust: From Ideal Types to Plural Forms," *Annual Review of Sociology,* 15 97–118.

Cha, Ariana Eunjung (2005). "In Retail, Profiling for Profit," *Washington Post,* August 17 A01.

Cox, Donald F. and Stuart U. Rich (1964). "Perceived Risk and Consumer Decision-Making—The Case of Telephone Shopping," *Journal of Marketing Research,* 1 (4) 32–39.

Cunningham, Lawrence F., James H. Gerlach, Michael D. Harper and Young FClifford E. (2005). "Perceived Risk and the Consumer Buying Process: Internet Airline Reservations," *International Journal of Service Industry Management,* 16 357–372, 3/4

Das, T.K. and Bing-Sheng Teng (2004). "The Risk-based View of Trust: A Conceptual Framework," *Journal of Business and Psychology,* 19 (1) 85–116.

Elsner, Ralf, Krafft Manfred and Huchzermeier Arnd (2003). "Optimizing Rhenania's Direct Marketing Business through Multilevel Modeling (DMLM) in a Multicatalog-Brand Environment," *Marketing Science,* 23 (2) 192–206.

Felvey, J (1982). "Cross-Selling by Computer," *Bank Marketing,* 25–27.

Frank, R.E., W.F. Massy and D.G. Morrison (1965). "Bias in Multiple Discriminant Analysis," *Journal of Marketing Research,* 2 250–258.

Gabarro, J.J (1978). "The Development of Trust, Influence, and Expectations," in *Interpersonal Behavior: Communication and Understanding in Relationships*, A. Athos and J. J. Gabarro eds. Englewood Cliffs, NJ: Prentice-Hall., 290–303.

Garbarino, Ellen and Mark S. Johnson (1999). "The Different Roles of Satisfaction, Trust, and Commitment in Customer Relationships," *Journal of Marketing,* 63 70–87.

[8] "Dove. Multi-Category Beauty Master Brand" http://www.retailwire.com.

Gehrt, Kenneth C., Laura.J. Yale and Diana.A. Lawson (1996). "The Convenience of Catalog Shopping: Is There more to it than Time?," *Journal of Direct Marketing,* 10 (4) 19–28.

Gonul, Fusun and Frenkel Ter Hofstede (2006). "How to Compute Optimal Mailing Decisions?," *Marketing Science,* 25 (1) 65–74.

Gonul, Fusun and Meng Ze Shi (1998). "Optimal Mailing of Catalogs: A New Methodology Using Estimable Structural Dynamic Programming Models," *Management Science,* 44 (9) 1249–1262.

Greene, William H. (2002). in *Econometric Analysis*, (5th ed.). Upper Saddle River, NJ: Prentice Hall.

Kamakura, Wagner A., Sridhar N. Ramaswami and Rajendra K. Srivastava (1991). "Applying Latent Trait Analysis in the Evaluation of Prospects for Cross-selling of Financial Services," *International Journal of Research in Marketing,* 8 329–349.

Keller, Kevin Lane and David A. Aaker (1992). "The Effects of Sequential Introduction of Brand Extensions," *Journal of Marketing Research,* 29 (1) 35–49.

Knott, Aaron, Hayes Andrew and Scott A. Neslin (2002). "Next-Product to Buy Models for Cross-Selling Applications," *Journal of Interactive Marketing,* 16 59–75 (Summer).

Kumar, V. and Kiran Karande (2000). "The Effect of Retail Store Environment on Retailer Performance," *Journal of Business Research,* 49 (2) 167–181.

Kumar, V. and Rajkumar Venkatesan (2005). "Who are the Multichannel Shoppers and how do they perform? Correlates of Multichannel Shopping Behavior," *Journal of Interactive Marketing,* 19 44–62 (Spring).

Kumar, V., Venkatesan Rajkumar and Reinartz Werner (2006). "Knowing What to Sell, When, and to Whom," *Harvard Business Review,* 1–8.

Li, Shibo, Sun Baohong and Ronald T. Wilcox (2005). "Cross-Selling Sequentially Ordered Products: An Application to Consumer Banking Services," *Journal of Marketing Research,* 42 (2) 233–239.

Mayer, R.C., J.H. Davis and F.D. Schoorman (1995). "An Integrative Model of Organizational Trust," *Academy of Management Review,* 20 709–734.

Moorman, Christine, Deshpande Rohit and Zaltman Gerald (1993). "Factors affecting Trust in Market Relationships," *Journal of Marketing,* 57 81–101.

Morgan, Robert M. and Shelby D. Hunt (1994). "The Commitment-Trust Theory of Relationship Marketing," *Journal of Marketing,* 58 20–38.

Ngobo, Paul Valentin (2004). "Drivers of Customers' Cross-Buying Intentions," *European Journal of Marketing,* 1129–1157, 38 (9/10).

Nooteboom, B (1996). "Trust, Opportunism, and Governance: A Process and Control Model," *Organization Studies,* 17 985–1010.

Pollatsck, A. and A Tversky (1970). "A Theory of Risk," *Journal of Mathematical Psychology,* 7 540–553.

Rapoport, A. and T.S Wallsten (1972). "Individual Decision Behavior," *Annual Review of Psychology,* 23 131–176.

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

Reinartz, Werner J. and V. Kumar (2002). "The Mismanagement of Customer Loyalty," *Harvard Business Review,* 1–13. July.

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

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

Selden, Larry and Geoffrey Colvin (in press). *Angel Customers & Demon Customers: Discover Which Is Which and Turbo-Charge Your Stock*. New York, NY: Penguin Group.

Senecal, Sylvain and Jacques Nantel (2004). "The Influence of Product Recommendations on Consumers' Online Choices," *Journal of Retailing,* 80 159–169.

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

Verhoef, Peter C. and Bas Donkers (2005). "The Effect of Acquisition Channels on Customer Loyalty and Cross-Buying," *Journal of Interactive Marketing,* Spring 19 31–43.

Verhoef, Peter C., Hans Franses Philip and Janny C. Hoekstra (2001). "The Impact of Satisfaction and Payment Equity on Cross-buying: A Dynamic Model for a Multi-service Provider," *Journal of Retailing,* 77 359–378.