J. Andrew Petersen & V. Kumar

Are Product Returns a Necessary Evil? Antecedents and Consequences

The firm–customer exchange process consists of three key parts: (1) firm-initiated marketing communications, (2) customer buying behavior, and (3) customer product return behavior. To date, the literature in marketing has largely focused on how marketing communications affect customer buying behavior and, to some extent, how past buying behavior affects a firm's decisions to initiate future marketing communications. However, the literature on product returns is sparse, especially in relation to analyzing individual customer product return behavior. Although the magnitude of the value of product returns is known to be high ($100 billion per year), how it affects customer buying behavior is not known because of a lack of data availability and understanding of the role of product returns in the firm–customer exchange process. Given that product returns are considered a hassle for a firm's supply chain management and a drain on overall profitability, it is important to study product return behavior. Thus, the authors empirically demonstrate the role of product returns in the exchange process by determining the exchange process factors that help explain product return behavior and the consequences of product returns on future customer and firm behavior. In addition, the authors demonstrate that product returns are inevitable but by no means evil.

Keywords: product returns, seemingly unrelated regression Tobit model, empirical application, latent class segmentation, power transformation

Product returns are an important and necessary part of the exchange process between companies and customers. In some cases, product lines have had return rates of greater than 25% (Hess and Mayhew 1997). Indeed, product returns cost U.S. manufacturers and retailers approximately $100 billion annually in lost sales and reverse logistics, reducing profits by 3.8% on average per retailer or manufacturer (Blanchard 2007). For this reason, many firms tend to treat product returns as a necessary evil of the firm–customer exchange process.

For example, Best Buy is well known for its list of "demon" customers at local stores. These customers are identified as those who have taken advantage of the product return process. Because of this, they have been blacklisted and are asked not to shop at Best Buy in the future (Boyle 2006). Best Buy is not the only firm to have made the news for cracking down on this behavior. Sprint recently decided that customers who overused customer service—in this context, customer complaints are similar to product returns of service—should have their contracts terminated (Reardon 2007). Sprint based the approximately 1000 contract cancellations on each customer's overuse of customer support, which can cost Sprint $2–$3 per minute. However, although Sprint and Best Buy reduced their losses on these specific customers, the impact of these actions on their future profitability is still unclear. This is because future profits not only are a function of current customer spending but also are affected directly by the loss in spending from customers who defect and the loss of potential new customers through negative word of mouth.

Many other firms have altered their return policies to fit their product return management strategy. For example, Wal-Mart allows customers to return products up to 90 days after purchase, with some exceptions, and Dell allows customers to return products within 21 days after purchase for a 15% restocking fee, also with some exceptions.[1] Even with these return policies, the number and complexity of product returns is increasing with the advent of online channels (Bonifield, Cole, and Schultz 2002). To combat this problem, many companies are beginning to manage supply chains to simplify the return process for consumers (Guide et al. 2006; Stock, Speh, and Shear 2002). This includes outsourcing the return process to third parties that specialize in reverse logistics, cutting costs by simplifying the return process, and even getting returned merchandise back out to the distribution channel to salvage some profits. Thus, although companies are addressing the issue of handling product returns by streamlining their logistics, the scarce research on product returns in marketing has focused mainly on optimal return policies for firms (Anderson, Hansen, and Simester 2009; Wood 2001), how return poli-

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[1]For a sample of the product return policies, see Web Appendixes W1 and W2 (http://www.marketingpower.com/jmmay09).

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cies can affect the decision to purchase now (Nasr-Bechwati and Siegal 2005), how these policies can affect customer repurchase behavior (Bower and Maxham 2006), and evidence that product returns provide customers with an option value that is measurable (Anderson, Hansen, and Simester 2009). In addition, although Bower and Maxham (2006) consider customer repurchase behavior, their study is based only on the first product return and lacks data on marketing interactions with customers.

What is clear from this prior research is that product return policies affect customer product return behavior, and in turn, customer product return behavior plays a significant role in the firm–customer exchange process. Prior research has shown that a lenient product return policy potentially creates a competitive advantage for the retailer or manufacturer (Padmanabhan and Png 1997) and increases a customer's likelihood to purchase a product in the first place (Chu, Gerstner, and Hess 1998; Nasr-Bechwati and Siegal 2005). However, a lenient product return policy is not always ideal (Wood 2001), because it can lead to more product returns (Davis, Hagerty, and Gerstner 1998) and to "abuse," which can cost the firm more than it benefits (Rust, Zahorik, and Keiningham 1996). In addition, if the relationship between the current customer product return behavior and future customer value were negative, managers could give disincentives for customers to return products to maximize profits. However, prior research has shown that product returns (up to a threshold) are positively related to a customer's future value to the firm (Reinartz and Kumar 2003; Venkatesan and Kumar 2004). The same result also holds true in the area of customer complaints (i.e., product returns of poor service), in which it is optimal to allow for customer complaints up to a threshold (Fornell and Wernerfelt 1987). This presents a challenge to managers on how to deal with customer product returns to maximize profits.

Thus, a better understanding is needed of the trade-offs that product returns can bring to the profitability of a firm. Are product returns a necessary evil because they force a firm to spend too much on reverse logistics and consume losses from the sales of returned merchandise, or are product returns potentially beneficial because they can add value to the firm by reducing a customer's purchase risk or through other positive behavioral consequences (e.g., higher repurchase behavior)? Thus far, research in marketing has not addressed the role of product returns in the exchange process, only that product returns affect the accurate estimation of customer demand and should not be ignored (Anderson, Hansen, and Simester 2009). In addition, there has been little research in marketing to establish metrics for managing customers strategically that include product returns. Thus, by answering the following three questions, this study can help firms manage customer product returns:

- What are the exchange process factors (i.e., marketing, transaction, and customer characteristics) that describe customer product return behavior?
- To what extent do product returns affect customers' future buying behavior and a firm's decision to allocate marketing resources?
- Are product returns a necessary evil for firms?

In Table 1, we summarize the contribution of this study with regard to several other studies that have focused on product returns and their impact on the exchange process.

A Conceptual Model of Marketing, Buying, and Product Returns

The general exchange process between a firm and a customer is made up of three distinct parts that occur continuously during the course of the customer relationship: (1) firm-initiated marketing communications, (2) customer buying behavior, and (3) customer product return behavior. The marketing literature has investigated how firm-initiated marketing communications affect customer buying behavior, whether through various types of advertising and sales promotion (e.g., Gupta 1988) or through direct marketing communications (e.g., Venkatesan and Kumar 2004). In addition, several studies have analyzed the impact of customer buying behavior on the firm's decision to conduct subsequent marketing activities (e.g., Elsner, Krafft, and Huchzermeier 2004). However, customer product return behavior has often been ignored. Thus, the conceptual framework for this study involves understanding the relationship among firm-initiated marketing communications, customer buying behavior, and customer product return behavior.

Although understanding the relationship among these three key parts of the exchange process can be complex, there tends to be an inherent order to the process. In almost all cases, firm-initiated marketing communications lead to a potential customer purchase, which in turn can potentially lead to a customer product return. As a result, we represent the firm–customer exchange process as a series of three ordered actions moderated by several factors. A firm's decision to send marketing communications is a function of past purchase and customer characteristics. Customer buying behavior is a function of marketing communications, past purchase, and customer characteristics. Customer product return behavior is a function of current customer purchases, past purchase, and customer characteristics (see Figure 1).

Theory and Hypothesis Development

In this section, we develop the hypotheses related to the antecedents and consequences of customer product return behavior; this is one of the main contributions of this study. We do not introduce any hypotheses related to a firm's decision to allocate marketing resources or a customer's decision to make purchases that are not related to product returns, because these issues are not the focus of this study.

Theory Development

We expect that each customer desires to maximize his or her utility when making decisions to purchase products. Thus, if we analyze the process of purchasing and returning products, we can separate this process into three distinct steps. First, firms send marketing communications to current and prospective customers to increase their awareness

TABLE 1
Summary of Prior Research Focused on Customer Product Return Behavior

Studies	Main Contributions Regarding Product Return Behavior
Hess, Chu, and Gerstner (1996)	•Show how to profitably control for merchandise returns by charging customers a nonrefundable fee for purchasing products (e.g., shipping cost).
Hess and Mayhew (1997)	•A model to predict when product returns will occur after purchases.
Padmanabhan and Png (1997)	•A study of the strategic effects of return policies on retail competition and profits for manufacturers.
Davis, Hagerty, and Gerstner (1998)	•Analytically identify why there is so much variation between product return policies across retailers.
Wood (2001)	•Return policy leniency increases purchase rates and product return rates for customers in remote purchase environments.
Bonifield, Cole, and Schultz (2002)	•Show a correlation between perceived quality of online retailers and product return policy leniency.
Nasr-Bechwati and Siegal (2005)	•The product return policy for a store is used by a customer as one of the signals for purchasing products.
Guide et al. (2006)	•Present a network flow with delay models that include the marginal value of time to identify the drivers of reverse supply chain design.
Bower and Maxham (2006)	•A field study showing that a customer who experiences a free-based product return is more likely to purchase more in the future than a customer who experiences a fee-based product return.
Anderson, Hansen, and Simester (2009)	•Provide empirical evidence that product returns give customers an option value that is measurable. •Provide empirical evidence to show how varying product return policies affect firm profits.
Anderson et al. (2008)	•Provide an economic model of customer purchase and return behavior. •Empirical evidence that customer return rates increase with price paid.
Current study	•Simultaneously models customer buying behavior, customer product return behavior, and a firm's decision to allocate marketing resources. •Identifies exchange process factors that describe product return behavior. •Identifies the consequences of product return behavior on future buying behavior and a firm's decision to allocate marketing resources.

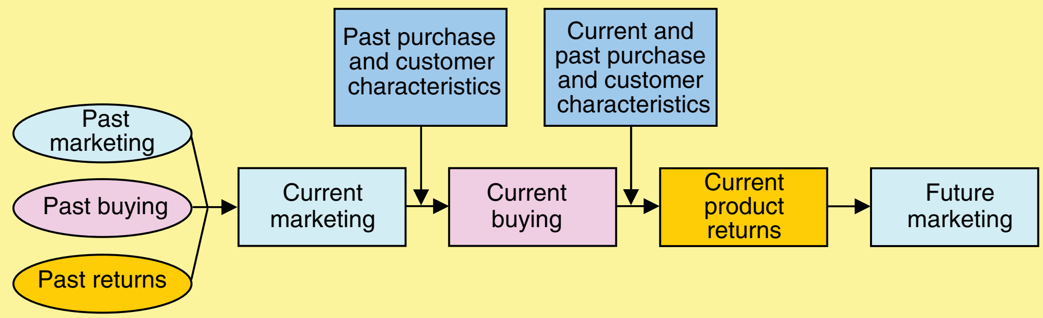
and heighten their interest in purchasing products from the firm. Second, a customer chooses to purchase a product, such that the perceived prepurchase utility of that product is positive. Third, after the customer has received the product, the customer evaluates the decision to purchase the product and determines whether the postpurchase utility is positive (keeps the product) or negative (returns the product). In this case, the utility of the product (both prepurchase and post-purchase utility) for a specific customer is derived from two parts: (1) the cost of the product, which is known to the firm and the customer at the time of purchase, and (2) the fit of the product, which is unknown to the firm but known to the customer after the purchase. The utility of a product for a specific customer can be understood as having a mean and a variance that are determined by the known (e.g., price of the product) and the unknown (e.g., uncertainty of product performance) factors related to the past and current purchase and customer characteristics. Thus, although we do not explicitly observe the factors that affect a customer's decision to return a product, we observe exchange process factors (i.e., marketing, purchase, and customer characteristics) that can help explain the mean and variance of each customer's postpurchase utilities and, in turn, each customer's expected product return behavior.

Antecedents of Product Returns

Because of the inherent order of product returns in the exchange process, as illustrated in the conceptual model (see Figure 1), we focus on customer buying behavior as the key driver of customer product returns. Although marketing communications may have some effect on customer product returns, it is more likely that this effect is indirect in nature. This is because marketing communications tend to influence customer buying behavior directly, which then influences customer product return behavior. Customers must buy products to return products, with only a few exceptions (e.g., gifts). Thus, we expect that as customers purchase more products, they will return more products. Although this has not been empirically tested at the customer level, the relationship between the number of purchases and the number of product returns is positive at the aggregate level (Bonifield, Cole, and Schultz 2002). This finding should not change at the customer level.

If it were simply the case that each customer returned approximately the same proportion of products, (i.e., if the ratio of products purchased to products returned was constant across customers), a positive relationship between purchase behavior and return behavior would be self-evident.

FIGURE 1
The Interrelationship of Marketing, Buying, and Product Returns



Where
•Past purchase characteristics = characteristics of previous purchases for customer i (e.g., average interpurchase time and multichannel shopping)
•Current purchase characteristics = characteristics of current purchases for customer i (e.g., product category and channel of purchase)
•Customer characteristics = demographic information of customer i (e.g., income)

However, if different customers return different amounts of products (research has shown a great variance in return behavior across customers; see, e.g., Hess and Mayhew 1997), it is important to understand the underlying relationship among customer purchase behavior, customer characteristics, and customer product return behavior. To do this, we develop hypotheses regarding several common exchange process factors related to product return behavior that help explain the mean and variance of a customer's postpurchase utility.

These factors include (1) gift purchases, (2) holiday purchases, (3) products purchases in new product categories (i.e., cross-buying), (4) products purchased in new distribution channels (i.e., multichannel shopping), (5) products purchased in new product categories and new distribution channels, and (6) products purchased on sale. Next, we discuss the details of each hypothesis and present them formally. Table 2 summarizes each hypothesis, noting the expected effect and the rationale for the effect.

Gifts. Products purchased as gifts, which are subsequently given to a third party, not only carry an economic value explicit in the price of the item purchased but also have added value from a social dimension (Sherry 1983). Consequently, even if the gift is not ideally what the recipient needs or even wants, the social dimension (or act of giving the gift) can decrease the postpurchase utility potentially less than if it were not a gift, resulting in fewer product returns. This occurs because the cost of returning the gift can cause tension in the relationship between the gift giver and the recipient. As a result, we propose the following:

H_1: Products received as gifts are less likely to be returned than products not received as gifts.

Holiday. Almost all products are seasonal. In many cases, especially for retail products, the peak season is during the November–December holiday time. As an example, the catalog retailer whose data we used for this study has more than 45% of all its sales during November and December, with no more than 10% of its sales in any other month of the year. For other industries, the peak season may vary. For example, accountants' peak service output is near March and April each year during tax season. However, for the most part, any discussion about seasonal effects tends to be related to economics and statistics, and prior research has usually tried to remove these effects from the data (Radas and Shugan 1998). However, not only does behavior accelerate during the peak season, but the decision to purchase certain types of products also likely varies with the season as well. As a result, many customers may purchase products in the peak season that are more likely not to fit expectations or products that the customer may find unnecessary after purchase, leading to a product return. However, many "regular" purchases during the year tend to follow a more well-defined purchase pattern. In addition, we expect that these regular purchases are products the customer is familiar with and frequently purchases. Thus, we propose the following:

H_2: Products purchased during the holiday season (i.e., November and December) are more likely to be returned than products purchased during the rest of the year.

Cross-buying. In this study, the act of cross-buying refers to a customer who purchases in a product category or department for the first time. For example, if a customer has purchased in the men's department and then purchases in the women's department, the customer engaged in cross-buying. Although cross-buying behavior has been shown to affect long-term buying behavior positively (Kumar, George, and Pancras 2008), we also expect it to affect a customer's product return behavior. Customers who buy in a new category for the first time are likely unfamiliar with the

TABLE 2
The Antecedents and Consequences of Product Returns

Hypothesis	Expected Effect	Antecedents: Rationale
H_1: Past gift → current product return	–	Gifts carry not only economic value but also social value (Sherry 1983). This social value (i.e., the gift giver–recipient relationship) may far outweigh the desire to return the product, even if it does not fit the needs/wants of the recipient.
H_2: Past holiday → current product return	+	Customers often purchase more during the peak holiday season; for this study the retailer's peak season is November–December. As a result, customers often buy significantly more than they do in the off-season and, in turn, are likely to return more products.
H_3: Past new cross-buy → current product return	+	Customers who make a purchases in an unfamiliar categories (in the same channel) are purchasing products in new categories that are less likely to fit their needs and, as a result, are more likely to return products.
H_4: Past new channel → current product return	–	Customers who make purchases in new distribution channels (not categories) are likely shifting familiar purchases to lower-cost or more convenient distribution channels. This makes it less likely for a purchase in a new channel to be returned.
H_5: Past new channel and cross-buy → current product return	+	Customers who buy new products in new channels are purchasing in unfamiliar categories and unfamiliar channels. As a result, it is more likely that there will be a misfit with the product or the purchase channel, causing a product return.
H_6: Past new sale items → current product return	–	Sale items cost less than regular-priced items. As a result, the perceived value hypothesis suggests that customers are more likely to return items when they pay a higher price than when they pay a lower price.
		Consequences: Rationale
H_7: Current product return → future buying behavior	∩	Prior research with a business-to-business firm has shown an inverted U-shaped relationship between the number of product returns and customer lifetime value (Venkatesan and Kumar 2004). Although this study is in a business-to-consumer context, we expect to find a similar relationship.
H_8: Current product return → future marketing resource allocation	–	When firms make decisions to allocate resources to marketing, they try to choose the optimal allocation method to maximize future profitability. As a result, we expect the firm to allocate fewer resources to customers who return products more products.

product purchased (i.e., added risk to the purchase process), especially in a catalog setting, in which the product cannot be tried before it is purchased. We expect this to be the case even if the customer is purchasing a product in the same distribution channel. If the customer has some level of uncertainty with the new product purchase in the new product category, we expect that the customer is more likely to return the product. Thus, we propose the following:

> H_3: Products purchased in new categories within the same distribution channel are more likely to be returned than products purchased in familiar categories within the same channel.

Multichannel shopping. In this study, a multichannel shopper is a customer who makes purchases across more than one distribution channel (e.g., telephone, catalog, Internet). Similar to cross-buying behavior, multichannel shopping has also been shown empirically to be positively related to future customer profitability (Venkatesan, Kumar, and Ravishanker 2007). However, we expect that customers who purchase in a new channel (but in the same product category) are purchasing familiar products through different distribution channels. For example, suppose a customer purchased a shirt in a retail outlet. If the customer purchases another of the same shirt from the retailer, he or she may choose to buy the next shirt through the Internet, which is more convenient than going to the retail store. In this case, we expect the customer to find less risk in the purchase because of the familiarity of the product being purchased, and in turn, the customer will be less likely to return the purchase from the new distribution channel. We also expect that when the customer shifts same-category purchases to another channel, it is likely that he or she is purchasing the same product at a lower cost or greater convenience. When a customer stays in the same distribution channel, though some of the products may be repurchases, he or she is also likely to be shopping across many different products in a given product category. Thus, we propose the following:

H_4: Products purchased in new distribution channels within the same product category are less likely to be returned than products purchased in familiar channels within the same product category.

Cross-buying and multichannel shopping. A customer who purchases a product in a new product category and a new distribution channel simultaneously is buying not only within an unfamiliar product category but also within an unfamiliar channel. Because the customer is facing two different unknowns, this likely compounds the uncertainty he or she faces, thus adding significant risk to the purchase. For example, if a customer is used to purchasing within the men's department in the retail store and makes a purchase from the children's department through the Internet, the unfamiliarity with both the product category and the distribution channel can cause the customer to be more likely to return the product. Thus, we propose the following:

H_5: Products purchased in new channels and new categories are more likely to be returned than products purchased in familiar channels and/or familiar product categories.

Sale items. Recent research has shown that customer return rates are not independent of the price a customer pays (Anderson et al. 2008). This supports the perceived value hypothesis, which suggests that as the price of the item increases, the customer becomes more likely to return a product that lacks fit. With respect to sale items, this suggests that items bought on sale are lower-priced items and are less likely to be returned by the customer. Thus, we propose the following:

H_6: Products purchased on sale are less likely to be returned than products purchased at regular price.

Consequences of Product Returns

It is also important to understand how a customer's decision to return or not to return a product affects his or her long-term relationship with a firm. We know that all purchases across the entire relationship with a firm have a certain level of uncertainty that is not known until after a purchase is made. We expect that for each customer, this level of uncertainty decreases over time as he or she becomes more familiar with the products the firm offers; this will occur regardless of whether the customer returns a product. In addition, a customer who returns a product satisfactorily will potentially be able to remove some additional uncertainty with future purchases by lowering the perceived risk of future purchases, knowing that products that do not fit can be returned without excess hassle. Thus, understanding past product return behavior should help explain future decisions by both the firm to allocate marketing resources and the customer to make future purchases and product returns.

Future buying. Recent research in marketing has shown that for a business-to-business setting, there is an inverted U-shaped relationship between the number of products returned and the customer's lifetime value (Venkatesan and Kumar 2004; Venkatesan, Kumar, and Bohling 2007). Although the setting of this study is a business-to-consumer catalog retailer, not a high-tech business-to-business firm, we expect to find the same relationship. Thus, we propose the following:

H_7: The amount of product returns is positively related to the amount of products purchased in the future, up to a threshold (an inverted U-shaped effect).

Future marketing. When firms make decisions to allocate resources to marketing, the optimal resource allocation method is set on the basis of the goal to maximize future customer profitability. This occurs regardless of whether it is a decision for acquisition and retention through direct marketing initiatives (Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001; Venkatesan and Kumar 2004), whether it is a decision pertaining to advertising and promotion expenditures (Berger and Nasr 1998; Berger and Nasr-Bechwati 2001), or when the firm is analyzing customer brand-switching behavior (Rust, Lemon, and Zeithaml 2004). In addition, firms often find that product returns (especially in the short run) are a drain on overall profitability because they are a loss of sales revenue and cost the firm resources for reverse logistics. As a result, when firms make decisions to allocate resources, we expect that as a customer returns more products, he or she will receive less consideration by the firm for marketing resources. Thus, we propose the following:

H_8: The amount of product returns is negatively related to the amount of marketing communications a customer receives in the future.

Methodology

A Model Describing the Role of Product Returns in the Exchange Process

In this section, we develop a model that helps describe the role of product returns in the exchange process between a firm and its customers. To choose the appropriate model for estimating the relationships among marketing communications, buying behavior, and product return behavior, we must first account for the key modeling challenges in this problem. Then, we introduce a general framework for estimating this model. Finally, we conduct an empirical application of the modeling framework by using actual customer data from a catalog retail firm.

Modeling Challenges

Simultaneity and endogeneity. The first challenge is the inherent ordering of the three key aspects of the exchange process (Figure 1), which creates an issue of a simultaneity bias that can affect the outcome of the model estimation. This occurs because each of the three dependent variables (marketing, buying, and product returns) is an explanatory variable in at least one of the other two equations. As a result, it is necessary to determine jointly the parameters for each model to remove any biases from simultaneity. Similarly, because of the inherent ordering of the three key aspects of the exchange process over time, there is a potential endogeneity bias that will affect the outcome of the model estimation. This can occur because the dependent variables within this system of equations are dependent on explanatory factors in the current period (t), while the same explanatory factors are dependent on the endogenous dependent variables in the last period (t – 1).

To account for the potential simultaneity and endogeneity biases that are present in this modeling framework, the model we choose needs to incorporate a system of equations that allows for simultaneous estimation of the three limited dependent variables in the three different models describing marketing communications, buying behavior, and product returns. In addition, each model needs to account for customer and firm behavior in the prior periods.

Censored data. The second challenge that needs to be addressed is that all three endogenous dependent variables in this model (product returns, buying, and marketing) have some values that are unobserved because the data are right censored. The data are right censored at a given time (August 2004), and we do not observe any product returns, buying behavior, or marketing communications after this time, even though the relationship may not have ended. As a result, we need to remove any bias from the parameter estimates in the model due to the censored nature of the data. To do this, we augment the censored data by drawing values from a truncated normal distribution for the model estimation (Wei and Tanner 1990). We need to account for the right-censoring problem only in this case because we use cohorts of customers who made their first purchases in a given year.

Truncated data. The third challenge we need to address is related to the truncation of the data. In this case, all three of the dependent variables in the model are left truncated at zero. This occurs because resources for marketing communications are either allocated (+) or not (0), buying behavior is either observed (+) or not (0), and product return behavior is either observed (+) or not (0). As a result, the data are not distributed normally, because their range includes all numbers greater than or equal to 0. This presents some issues of estimation bias. However, the solution to this problem is straightforward because it was in the data-censoring case. Similar to the solution to the data-censoring problem, this truncation problem can also be solved through data augmentation (Wei and Tanner 1990). The data that are truncated at 0 can be augmented by drawing values from a truncated normal distribution to remove any bias in the estimation procedure.

Skewness. In addition to using the augmented endogenous variables as dependent variables in each of the three equations, we use these variables as independent variables. We use squares of the augmented variables to determine whether we uncover any saturation effects in the analysis. Using the squared augmented variables creates a problem of right skewness, compared with the squared values of the original endogenous variables. However, we correct for this issue by using a cube root power transformation of the squared augmented variable (Chen and Deo 2004). The result of this power transformation is a variable that more closely approximates the distribution of values of the original squared endogenous variable. The details on this power transformation are available in Appendix A.

Heterogeneity. The final challenge we need to consider is that of heterogeneity, both unobserved and observed. To account for observed heterogeneity, we include several demographic variables (e.g., income) in each of the three models. To account for unobserved heterogeneity, we chose latent class segmentation. This latent class segmentation helps us determine how many latent segments of customers exist after we account for the variance in marketing, buying, and product returns using a set of exogenous predictors, lagged endogenous predictors, customer characteristics, and demographics.

The Seemingly Unrelated Regression Tobit Model

To account for the key modeling challenges described in the previous section, we propose the following seemingly unrelated regression (SUR) Tobit model:

$$\text{(1)} \quad \begin{aligned} PR^*_{it} &= \alpha_0 + \alpha_1 Buy^*_{i,t-1\to t} + \alpha_2 (Buy^{*2}_{i,t-1\to t})^{1/3} \\ &\quad + \alpha_3 PR^*_{i,t-1} + \alpha_4 (PR^{*2}_{i,t-1})^{1/3} + \beta' Z_{PR} \\ &\quad + \varepsilon_{PR}, \end{aligned}$$

$$\text{(2)} \quad \begin{aligned} Buy^*_{i,t-1\to t} &= \delta_0 + \delta_1 Mktg^*_{i,t-1\to t} \\ &\quad + \delta_2 (Mktg^{*2}_{i,t-1\to t})^{1/3} \\ &\quad + \delta_3 Buy^*_{i,t-2\to t-1} \\ &\quad + \ldots\ \delta_4 (Buy^{*2}_{i,t-2\to t-1})^{1/3} \\ &\quad + \delta_5 PR^*_{i,t-1} + \delta_6 (PR^{*2}_{i,t-1})^{1/3} \\ &\quad + \lambda' Z_{Buy} + \varepsilon_{Buy}, \text{ and} \end{aligned}$$

$$\text{(3)} \quad \begin{aligned} Mktg^*_{i,t-1\to t} &= \omega_0 + \omega_1 Mktg^*_{i,t-2\to t-1} \\ &\quad + \omega_2 (Mktg^{*2}_{i,t-2\to t-1})^{1/3} \\ &\quad + \omega_3 Buy^*_{i,t-2\to t-1} \\ &\quad + \ldots\ \omega_4 (Buy^{*2}_{i,t-2\to t-1})^{1/3} \\ &\quad + \omega_5 PR^*_{i,t-1} + \omega_6 (PR^{*2}_{i,t-1})^{1/3} + \phi' Z_{Mktg} \\ &\quad + \varepsilon_{Mktg}, \end{aligned}$$

where

$$(\varepsilon_{PR}, \varepsilon_{Buy}, \varepsilon_{Mktg})' \sim iidN(0, \Omega),$$

PR^*_{it} = the value of the augmented endogenous variable Product Returns,

$(PR^{*2}_{it})^{1/3}$ = the transformed value of the squared augmented endogenous variable Product Returns,

$Buy^*_{i,t-1\to t}$ = the value of the augmented endogenous variable Buy,

$(Buy^{*2}_{i,t-1\to t})^{1/3}$ = the transformed value of the squared augmented endogenous variable Buy,

$Mktg^*_{i,t-1\to t}$ = the value of the augmented endogenous variable Marketing,

$(Mktg^{*2}_{i,t-1\to t})^{1/3}$ = the transformed value of the squared augmented endogenous variable Marketing, and

$Z_{PR}, Z_{Buy}, Z_{MKTG}$ = the exogenous variables, lagged-endogenous variables, and covariates used as predictors for each of the three equations.

For this model, the first regression in the SUR model has product returns (PR^*_{it}) as the augmented dependent variable. In this case, product returns are a function of a customer's past purchase behavior ($Buy^*_{i,t-1 \to t}$), past product return behavior, and the characteristics of the purchase behavior (Z_{PR}). For the second equation, a customer's buying behavior is a function of the marketing spent on a given customer ($Mktg^*_{i,t-1 \to t}$), the customer's past buying and product return behavior, and other characteristics of the customer's purchase behavior (Z_{Buy}). The augmented dependent variable of the third model is the firm's allocation of marketing resources to a customer. This is a function of past customer purchase behavior, product return behavior, and past marketing resources allocated to the customer. We also use the transformed squared augmented variables as independent variables in each of the three equations. To estimate this model, we incorporate a Monte Carlo expectation-conditional maximization (MCECM) algorithm as detailed in Appendix B.

An Empirical Application

The data we used for this study come from a business-to-consumer company that sells many different categories of products through the Internet, catalogs, telephone, and retail outlets. The company's return policy is considered lenient in that it is willing to give a full refund or an exchange if, for any reason, the customer may not want to keep the product at any time after purchase. We include only product returns, not exchanges, in the empirical application of this study. These data contain information on all the transactions that occurred between January 1998 and August 2004. For the purpose of testing and validation, we use two cohorts of customers who made their first purchase any time during either 1998 (Cohort 1) or 1999 (Cohort 2) and who made at least three purchases from the company between the time of their first purchase and August 2004. We dropped customers with fewer than three purchases because the objective of this research is to understand how buying, returning, and marketing affect the long-term customer–firm relationship and not just isolated incidents of buying and returns. Next, we describe the data; we also provide descriptive statistics of each cohort in Table 3.

Cohort 1. The data for Cohort 1 (whose first purchase was in 1998) include 1572 customers with a total of 25,178 products purchased—on average, slightly more than 16 products per customer. These purchases generated $1.08 million in revenue, or approximately $43 per purchase. Cohort 1 also includes 4113 products returned—on average, slightly more than 2.4 products returned per customer. These returned products generated a loss of revenue of $196,000, or approximately $48 per product return. This means that, on average, approximately 1 of every 6 products purchased was returned for either a refund or an exchange (4113/25,178), falling within the range (4%–25%) that direct marketers should expect (Fenvessy 1992). In addition, these customers received 135,949 catalogs—that is, approximately 86 catalogs per customer, or 13 catalogs per customer per year (over 6.75 years).

TABLE 3
Descriptive Statistics for Cohort 1 and Cohort 2

	Cohort 1 (1998)	Cohort 2 (1999)
Customers	1572	1586
Catalogs sent	135,949	118,867
Purchases (number)	25,178	23,368
Purchases (value)	$1.08 million	$1.0 million
Product returns (number)	4113	3394
Product returns (value)	$196,000	$169,000

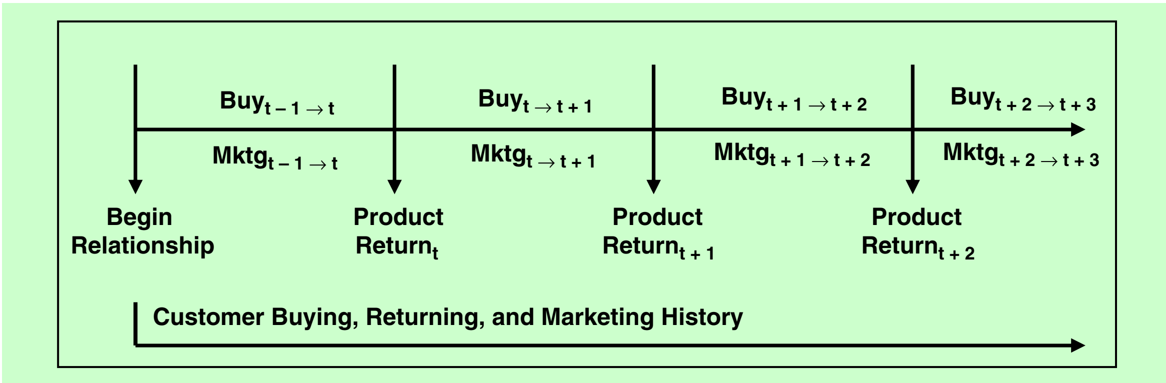
Cohort 2. The data for Cohort 2 (whose first purchase was in 1999) include 1586 customers, who purchased a total of 23,368 products—on average, approximately 15 products per customer. These purchases generated $1.0 million in revenue, or approximately $43 per purchase. Cohort 2 also includes 3394 products returned—on average, slightly more than 2.6 products returned per customer. These returned products generated a loss of revenue of $169,000, or approximately $50 per product return. This means that, on average, approximately 1 of every 7 products purchased was returned for either a refund or an exchange (3394/23,368), falling within the range (4%–25%) that direct marketers should expect (Fenvessy 1992). In addition, these customers received 118,867 catalogs—that is, approximately 75 catalogs per customer, or 13 catalogs per customer per year (over 5.75 years).

To model the data appropriately, we organized the data by the time of the product return of each customer with the company (see Figure 2). We set up the data in this way instead of using a cross-sectional time-series setup (i.e., monthly or quarterly) for two reasons. First, many customers (approximately 30%) have never returned a product. This means that each of these customers would have no variation in the product return variable. Second, we would be unable to determine the order of occurrence if a product return occurred in the same month or quarter as a purchase. In one case, the purchase could have led to the product return, and in the other, the purchase could have happened immediately after the product return. As a result, we chose to model the data in which the product return occasion marks the interval of time.

For example, if a customer made three product returns in his or her lifetime, there would be a product return at time t, t + 1, and t + 2 (see Figure 2). Then, there would also be information about marketing communications and buying behavior before and after each product return. To operationalize the marketing communication, buying behavior, and product return behavior variables for each customer (time between returns can vary greatly), we divide the variables by the number of months since the previous product return (or since the start of the relationship if it is the first product return) by each customer. This gives a variable that describes the average monthly marketing communications, average monthly buying behavior, and average monthly product return behavior, which are observed and computed for each product return.

In Table 4, Panels A–C, we provide a description of all the variables in the three models and their operationalizations in which the independent variables chosen for the $Buy^*_{i,t-1 \to t}$ model are based on variables used in studies

FIGURE 2
Data Setup for a Sample Customer



Notes: Unit of observation is observed at each product return occasion.

that analyze the determinants of customer buying behavior (Reinartz and Kumar 2003; Venkatesan and Kumar 2004). We then use the information before each product return to determine what types of firm actions and customer behaviors lead to customers returning (or not returning) products.

Results

Model Fit

After dividing each of the cohorts into calibration (75% of the customers) and holdout (25% of the customers) samples, we estimated three different models for each of the two cohorts. Because the fit and the parameter estimates for both cohorts were similar, we provide only the results from the Cohort 1 in the article.[2] Thus, the sample for Cohort 1 (1998) includes 1179 customers with 3251 observations in the calibration sample and 393 customers with 1088 observations in the holdout sample. The three models we estimate for this analysis include the following:

1. Two equations of marketing and buying without product returns as an independent variable (Model 1).
2. Two equations of marketing and buying with product returns as an independent variable (Model 2).
3. Three equations of marketing, buying, and product returns (focal model of this study) (Model 3).

We first estimated these models in the SUR Tobit modeling framework using a latent class segmentation approach. We describe this latent class approach and provide the results of the analysis in Appendix C. From the results of the latent class analysis, we found that the optimal number of latent segments for our model was one. We chose the optimal number of segments on the basis of the model with the lowest consistent Akaike information criterion (CAIC) (Jedidi, Ramaswami, and DeSarbo 1993). Thus, we provide the results of model fit and parameter estimates in the main section of this article for only the one-segment model. This suggests that the predictor variables used in this study account for the heterogeneity across customers, even when the variance in the amount of product returns is high. For any future studies, it is still desirable to use the latent class segmentation approach first to determine whether there are multiple latent segments of customers.

In Table 5, we report the parameter estimates from the three models along with the R-square values for each equation within each SUR Tobit model. For our first observation, we find that the demographic variables (Married_i and Income_i) are nonsignificant for all three equations and in all three models. In addition, the ($\text{Buy}^{*2}_{i,t-1 \rightarrow t}$) variable is not as significant as a squared lagged endogenous variable in the Buy* equation across all three models.

We also find that between Model 1 and Model 2, by adding product returns as an independent variable, we can significantly increase the variance explained by each equation. For the $\text{Mktg}^*_{i,t-1 \rightarrow t}$ equation, the R-square increases from .263 to .280, and for the $\text{Buy}^*_{i,t-1 \rightarrow t}$ equation, the R-square increases from .381 to .410. When we introduce the third equation PR^*_{it} to the SUR Tobit model (Model 3), there is some improvement in the variance explained beyond that of Model 2 for the $\text{Mktg}^*_{i,t-1 \rightarrow t}$ and $\text{Buy}^*_{i,t-1 \rightarrow t}$ equations, up to .290 and .421, respectively. We do not expect this increase to be large, because the models have the same predictor variables. However, adding the PR^*_{it} equation helps improve the efficiency of the model estimation and helps account for additional covariance between equations. Finally, we observe a good fit ($R^2 = .371$) in the PR^*_{it} equation in Model 3. This suggests that the predictors explain a significant amount of the variance for customer product return behavior.

Although the results from the three models show that product returns play a key role in the exchange process, it is also important to show the consequences of not including product returns as a variable (dependent or independent) in the analysis. In other words, what additional value comes from including product returns in the study? To analyze the impact of including product returns, we compare the predictive results of the three models.

We compare the mean absolute deviation (MAD) in these three models' ability to predict marketing, buying, and

[2]The results from Cohort 2 are available on request.

TABLE 4
Variable Operationalization

A: The Marketing Model

Variable	Operationalization
Model: $Mktg^{*}_{i,t-1 \rightarrow t}$ (Average monthly catalogs sent to customer i from time t to time t – 1)	
$Buy^{*}_{i,t-2 \rightarrow t-1}$	Average monthly spending in dollars for customer i from time t – 2 to time t – 1
$(Buy^{*2}_{i,t-2 \rightarrow t-1})^{1/3}$	Cube root transformed squared average monthly spending in dollars for customer i from time t – 2 to time t – 1
$PR^{*}_{i,t-1}$	Average monthly product returns in dollars for customer i at time t – 1
$(PR^{*2}_{i,t-1})^{1/3}$	Cube root transformed squared average monthly product returns in dollars for customer i at time t – 1
$Mktg^{*}_{i,t-2 \rightarrow t}$	Average monthly catalogs sent to customer i from time t – 2 to time t – 1
$(Mktg^{*2}_{i,t-2 \rightarrow t-1})^{1/3}$	Cube root transformed squared average monthly catalogs sent to customer i from time t – 1 to time t
$Married_i$	Whether (1) or not (0) customer i is married
$Income_i$	Income of customer i

B: The Buy Model

Variable	Operationalization
Model: $Buy^{*}_{i,t-1 \rightarrow t}$ (Average monthly spending in dollars for customer i from time t – 1 to time t)	
$Mktg^{*}_{i,t-1 \rightarrow t}$	Average monthly catalogs sent from to customer i time t – 1 to time t
$(Mktg^{*2}_{i,t-2 \rightarrow t-1})^{1/3}$	Cube root transformed squared average monthly catalogs sent to customer i from time t – 1 to time t
$Buy^{*}_{i,t-2 \rightarrow t-1}$	Average monthly spending in dollars for customer i from time t –2 to time t – 1
$(Buy^{*2}_{i,t-2 \rightarrow t-1})^{1/3}$	Cube root transformed squared average monthly spending in dollars for customer i from time t – 2 to time t – 1
$PR^{*}_{i,t-1}$	Average monthly product returns in dollars for customer i at time t – 1
$(PR^{*2}_{i,t-1})^{1/3}$	Cube root transformed squared average monthly product returns in dollars for customer i at time t – 1
AIT_{it}	Average interpurchase time in months for customer i since first purchase until time t
AIT^{2}_{it}	Squared average interpurchase time in months for customer i since first purchase until time t
$(CB \times MC)_{i,t-1 \rightarrow t}$	Interaction of cross-buy and multichannel for customer i from time t – 1 to time t
$Married_i$	Whether (1) or not (0) customer i is married
$Income_i$	Income of customer i

C: The Product Return Model

Variable	Operationalization
Model: PR^{*}_{it-1} (Average monthly product returns in dollars for customer i at time t – 1)	
$Buy^{*}_{i,t-1 \rightarrow t}$	Average monthly spending in dollars for customer i from time t – 1 to time t
$(Buy^{*2}_{i,t-2 \rightarrow t-1})^{1/3}$	Cube root transformed squared average monthly spending in dollars for customer i from time t – 1 to time t
$PR^{*}_{i,t-1}$	Average monthly product returns in dollars for customer i at time t – 1
$(PR^{*2}_{i,t-1})^{1/3}$	Cube root transformed squared average monthly product returns in dollars for customer i at time t – 1
$Gift_{i,t-1 \rightarrow t}$	The number of gifts purchased by customer i from time t – 1 to time t
$Holiday_{i,t-1 \rightarrow t}$	Number of items purchased during November–December for customer i from time t – 1 to time t
$CBNew_{i,t-1 \rightarrow t}$	Percentage of the amount spent on products in new categories with no new channel purchases for customer i from time t – 1 to time t
$ChanNew_{i,t-1 \rightarrow t}$	Percentage of the amount spent on products in new channels with no new category purchases for customer i from time t – 1 to time t
$NewCBCH_{i,t-1 \rightarrow t}$	Percentage of the amount spent on new category and new channel purchases for customer i from time t – 1 to time t
$SalesItems_{i,t-1 \rightarrow t}$	Number of items purchased on sale for customer i from time t – 1 to time t
$TopCat_{i,t-1 \rightarrow t}$	The number of transactions in this retailer's most frequently purchased category for customer i from time t – 1 to time t
$TopChan_{i,t-1 \rightarrow t}$	The number of transactions in this retailer's most frequently purchased channel for customer i from time t – 1 to time t
$Married_i$	Whether (1) or not (0) customer i is married
$Income_i$	Income of customer i

product returns by using the parameter estimates from the results to predict the dependent variables in the holdout sample. Because there is no equation for product returns as a dependent variable in the first two models, it is evident

TABLE 5
Results from the Estimation Using Calibration Sample (75% of Households)

	Model 1	Model 2	Model 3
Dependent Variable: $\text{Mktg}^*_{i,t-1\rightarrow t}$			
Intercept	**.523 (.106)**	**.711 (.105)**	**.888 (.105)**
$\text{Buy}^*_{i,t-2\rightarrow t-1}$	**.029 (.001)**	**.028 (.001)**	**.025 (.001)**
$(\text{Buy}^{*2}_{i,t-2\rightarrow t-1})^{1/3}$	**–.010 (.002)**	**–.010 (.002)**	**–.031 (.012)**
$\text{PR}^*_{i,t-1}$		**–.024 (.002)**	**–.026 (.002)**
$(\text{PR}^{*2}_{i,t-1})^{1/3}$		**.095 (.022)**	**.046 (.023)**
$\text{Mktg}^*_{i,t-2\rightarrow t}$	**–.463 (.079)**	**–.376 (.078)**	**–.463 (.078)**
$(\text{Mktg}^{*2}_{i,t-2\rightarrow t-1})^{1/3}$	**.416 (.130)**	**.385 (.112)**	**.389 (.135)**
Married_i	*.098 (.069)*	*.063 (.068)*	*.030 (.100)*
Income_i	*–.001 (.001)*	*–.002 (.002)*	*–.001 (.001)*
Model fit: R-square	.263	.280	.290
Dependent Variable: $\text{Buy}^*_{i,t-1\rightarrow t}$			
Intercept	**–9.400 (3.225)**	**–11.728 (3.283)**	**–4.417 (2.118)**
$\text{Mktg}^*_{i,t-1\rightarrow t}$	**17.901 (.949)**	**18.132 (.962)**	**8.719 (1.053)**
$(\text{Mktg}^{*2}_{i,t-2\rightarrow t-1})^{1/3}$	**–.618 (.058)**	**–.584 (.059)**	**–.464 (.064)**
$\text{Buy}^*_{i,t-2\rightarrow t-1}$	**.296 (.031)**	**.291 (.032)**	**.384 (.036)**
$(\text{Buy}^{*2}_{i,t-2\rightarrow t-1})^{1/3}$	*–.040 (.076)*	*–.042 (.078)*	*–.062 (.040)*
$\text{PR}^*_{i,t-1}$		**.267 (.072)**	**.393 (.073)**
$(\text{PR}^{*2}_{i,t-1})^{1/3}$		**–.089 (.004)**	**–.062 (.004)**
AIT_{it}	**17.237 (1.091)**	**17.143 (1.090)**	**24.464 (1.187)**
AIT^2_{it}	**–.523 (.063)**	**–.520 (.063)**	**–.751 (.068)**
$(\text{CB} \times \text{MC})_{i,t-1\rightarrow t}$	**1.146 (.275)**	**1.125 (.282)**	**1.623 (.309)**
Married_i	*–2.369 (2.024)*	*–1.964 (2.025)*	*1.635 (2.026)*
Income_i	*.053 (.271)*	*.052 (.271)*	*.044 (.270)*
Model fit: R-square	.381	.410	.421
Dependent Variable: PR^*_{it}			
Intercept			**18.040 (1.614)**
$\text{Buy}^*_{i,t-1\rightarrow t}$			**.374 (.012)**
$(\text{Buy}^{*2}_{i,t-2\rightarrow t-1})^{1/3}$			**–.069 (.002)**
$\text{PR}^*_{i,t-1}$			**.163 (.030)**
$(\text{PR}^{*2}_{i,t-1})^{1/3}$			**–.058 (.010)**
$\text{Gift}_{i,t-1\rightarrow t}$			**–1.057 (.328)**
$\text{Holiday}_{i,t-1\rightarrow t}$			**8.366 (1.074)**
$\text{CBNew}_{i,t-1\rightarrow t}$			**.079 (.023)**
$\text{ChanNew}_{i,t-1\rightarrow t}$			**–.085 (.026)**
$\text{NewCBCH}_{i,t-1\rightarrow t}$			**.006 (.001)**
$\text{SaleItems}_{i,t-1\rightarrow t}$			**–1.264 (.238)**
$\text{TopCat}_{i,t-1\rightarrow t}$			**–9.683 (.921)**
$\text{TopChan}_{i,t-1\rightarrow t}$			**–8.988 (.991)**
Married_i			*–1.247 (.921)*
Income_i			*–.009 (.012)*
Model fit: R-square	N.A.	N.A.	.371

Notes: Numbers in cells are means (standard deviations). Italics denote nonsignificance, and bold entries are significant at $p < .01$. N.A. = not applicable.

that the predictive accuracy of product returns in the third model is always better. However, it is also important to determine whether there are gains in the predictive accuracy of marketing and buying behavior among the three models when product returns are entered first as independent variables and then as a dependent variable in a third equation (see Table 6).

As Table 6 shows, there is an improvement in the MAD from Model 1 (two equations without product returns), which had a MAD of 1.23 for $\text{Mktg}^*_{i,t-1\rightarrow t}$ and 36.64 for $\text{Buy}^*_{i,t-1\rightarrow t}$, to Model 2, which had a MAD of 1.19 for $\text{Mktg}^*_{i,t-1\rightarrow t}$ and 35.41 for $\text{Buy}^*_{i,t-1\rightarrow t}$. There is also an improvement in the MAD from Model 2 (two equations with product returns), which had a MAD of 1.19 for $\text{Mktg}^*_{i,t-1\rightarrow t}$ and 35.41 for $\text{Buy}^*_{i,t-1\rightarrow t}$, to Model 3, which had a MAD of 1.07 for $\text{Mktg}^*_{i,t-1\rightarrow t}$ (a 10% improvement) and 29.74 for $\text{Buy}^*_{i,t-1\rightarrow t}$ (a 16% improvement). In addition, we can predict PR^*_{it} in Model 3, which had a MAD of

TABLE 6
Predictive Accuracy for Models With and Without Product Returns Using Estimates from Calibration Sample (75%) to Predict Holdout Sample (25%) (MAD)

Models	$Mktg^*_{i,t-1\rightarrow t}$ (Average Number of Catalogs/Month)	$Buy^*_{i,t-1\rightarrow t}$ (Average Dollars Spent/Month)	PR^*_{it} (Average Dollars of Returns/Month)
$Mktg^*_{i,t-1\rightarrow t}$ and $Buy^*_{i,t-1\rightarrow t}$ (without product returns)	1.23	36.64	N.A.
$Mktg^*_{i,t-1\rightarrow t}$ and $Buy^*_{i,t-1\rightarrow t}$ (with product returns)	1.19	35.41	N.A.
$Mktg^*_{i,t-1\rightarrow t}$, $Buy^*_{i,t-1\rightarrow t}$, and PR^*_{it}	1.07	29.74	14.89

Notes: N.A. = not applicable.

14.89. Again, this shows that product returns are vital to understanding the exchange process not only when we try to predict product return behavior but also when we predict a firm's decision to allocate resources and a customer's decision to purchase over time.

Hypothesis Testing: Antecedents of Product Returns

Gift. Products received as gifts were returned less frequently than products not received as gifts, confirming H_1. The coefficient of $Gift_{i,t-1\rightarrow t}$ was –1.057. This suggests that each additional gift purchased leads to a decrease of approximately $1.06 in product returns per month. The reason this happens is likely that products received as gifts have an added value beyond that of the practical utility of the product. This added value is a result of the relationship between the gift giver and the gift recipient (Sherry 1983), which causes the recipient to have an additional attachment to the gift, making it less likely to be returned.

Holiday. Products purchased during the holiday season—in this case, November and December—were significantly more likely to be returned than products purchased during the rest of the year, confirming H_2. The coefficient on $Holiday_{i,t-1\rightarrow t}$ was 8.366. This means that, on average, for every item purchased during the holiday season, the average dollars in product returns per month increase by $8.37. This suggests not only that more products are purchased during the holiday season but also that the product type and reason for the product purchase are different for the holiday season than for the rest of the year. Furthermore, to validate this reason, we examined the data for several customers in the sample. For each customer, the products purchased during the months from January to October tended to be repurchases of the same or similar products each year. However, in November and December, not only did the customer purchase more products in total, but he or she also purchased products that were previously not purchased both in the same product category and in new product categories.

New cross-buy. When customers purchased more in new categories than in familiar categories, but in the same distribution channel, they were more likely to return more products. The coefficient on $CBNew_{i,t-1\rightarrow t}$ was .079. This means that for each percentage point increase in the proportion of products purchased in new categories since the last product return, the average monthly product return value increases by $.08. This matches our expectation in H_3. It shows that as customers increase their purchases from new categories, their product return behavior also increases. However, this is not necessarily a troubling finding, because research has shown that as customers shop in more categories, they buy proportionately more than customers who buy only in a single category (Kumar, George, and Pancras 2008).

New channel. When customers purchased more in new channels than in familiar channels, but in familiar product categories, they returned fewer products. The coefficient on $ChanNew_{i,t-1\rightarrow t}$ was –.085. This means that for each percentage point increase in the proportion of products purchased in new channels since the last product return, the average monthly product return value decreases by $.09. This matches our expectation in H_4. When examining the data, we observed that customers who purchased in a new distribution channel but within the same product category were usually purchasing the same products and just shifting the purchase to a new distribution channel. This often occurs when customers shift to a new channel with increased convenience or reduced risk.

New cross-buy and new channel. When a customer purchased more products in new distribution channels and new product categories, there was an increase in product return behavior, confirming H_5. The coefficient on $NewCBCH_{i,t-1\rightarrow t}$ was .006. This means that for each percentage point increase in the proportion of products purchased in new categories and new channels since the last product return, the average monthly product return value increases by $.01. Although we find that the relationship is positive, this does not necessarily mean that customers who buy in new product categories and new distribution channels at the same time are bad customers because they return too many products. First, even if the customer purchased all products since the past product return in new categories and channels (100%), it means an increase in average monthly product returns of only $1.00. Second, customers who are willing to venture into these new and unfamiliar areas are also more likely to increase their spending at a higher rate than customers who purchase only in familiar channels or categories (Kumar, George, and Pancras 2008; Venkatesan, Kumar, and Ravishanker 2007).

Items on sale. Customers who purchased products on sale returned fewer products than customers who purchased products at regular price. The coefficient on $\text{SaleItems}_{i,t-1 \to t}$ was –1.264. This means that for each item purchased on sale, the average value of products returned per month decreased by $1.26. This result matched our expectation in H_6. Customers who buy products on sale perceive less value in the product, which is likely to decrease the chance that the postpurchase utility becomes negative, resulting in fewer returns.

Hypothesis Testing: Consequences of Product Returns

Buy. The amount of products a customer returns now positively affects (up to a threshold) the number of products he or she purchases in the future, confirming H_7. The coefficient on PR^*_{it} was .393, and the coefficient on $(PR^{*2}_{it})^{1/3}$ was –.062. Thus, for every $1.00 increase in average monthly product return behavior, there is an increase (up to a threshold) of approximately $.39 in customer purchase behavior, which begins to decrease at a slow rate for each additional $1.00 of products returned. This means that customers who return a moderate amount of products tend to purchase the largest amount of products in the future. This adds to the empirical evidence in the marketing literature that shows a positive relationship between product return behavior and customer lifetime value (Venkatesan and Kumar 2004). The implications of this finding can be significant to managers with regard to return policy leniency (Wood 2001) and the optimal level of "hassle" in the product return process (Davis, Hagerty, and Gerstner 1998). This does not necessarily mean that lenient return policies are always ideal, but for this retailer, return policy leniency has a desirable effect on a customer's future purchase behavior. The satisfaction received through a free-based product return leads a customer to feel less risk, providing the firm another positive "touchpoint" to build the relationship.[3]

Marketing. The amount of products a customer returns negatively affects (up to a threshold) the number of catalogs a customer receives, confirming H_8. The coefficient on $PR^*_{i,t-1}$ was –.026, and the coefficient on $(PR^{*2}_{i,t-1})^{1/3}$ was .046. This means that each increase of $1.00 of average monthly product returns causes the firm to send approximately .026 fewer catalogs per month, up to a threshold. Although this is a fairly small effect, it still shows that as a customer returns more products, the firm reduces the number of catalogs the customer receives. The potential pitfall of this decision lies in the finding that the amount of products returned has a positive effect on the customer's future buying behavior (see H_7). As a result, reducing the marketing resources to customers who return too many products also potentially reduces the number of products these customers will purchase in the future. The firm could be realizing a suboptimal amount of value from its customers. To fix this problem, the decision to allocate resources should not be based independently on the amount of purchases a customer makes or the amount of products a customer returns but rather on maximizing the difference in value between the amount of products purchased and the amount of products returned.

Are Product Returns a Necessary Evil?

Although product returns cost the firm in terms of both profits from sales and reverse logistics, this study also empirically shows that up to a threshold, increases in product return behavior increase future customer purchase behavior. To understand the impact of these findings fully, it is also important to understand how increases and decreases in customer product return behavior affect firm profits. Thus, it is necessary to understand exactly what the tradeoff is between customer product return behavior and firm profits. In the process, we can also determine exactly what level of product returns maximizes profits for the focal firm of this study. To do this, we used the data from Cohort 1 to simulate the impact of changes in customer product return behavior on firm profits. We first computed the discounted firm profit from this sample of customers as follows:

$$\begin{aligned}\text{Firm profit} = \Big[&(\text{Purchase value} \times \text{margin}) \\ &- \text{Cost of product return} - \text{Marketing costs}\Big] \Big/ \\ &\Big[\text{Discount rate (15\%)}\Big],\end{aligned}$$

where

Firm profit = the total discounted profit from a given set of customers,
Purchase value × margin = the total profit from all purchases from customers in the sample,
Cost of product return = the total profit lost from product returns from customers in the sample (i.e., loss of sales revenue and cost of reverse logistics [return shipping]),
Marketing costs = the total costs of marketing to all customers in the sample, and
Discount rate = 15% per annum (each profit from purchase, cost of product return, and marketing cost was discounted to present value in the first year of the sample of customers).

We then allowed the overall percentage of the products returned by all customers in Cohort 1 to increase and decrease from the original percentage of product returns, which was 16%. According to the current level of product returns, the 1572 customers in Cohort 1 provide a discounted profit of $91,829 (see Table 7). After varying the amount of product returns each customer made, we found

[3]A free-based product return means that the customer pays no cost to the store to return the product.

TABLE 7
The Effect of Changes in Product Returns on Firm Profits

Change in Product Return Amount	Firm Profits (Cohort 1 – n = 1572)	Firm Profits (Customer Base – n = 1 million)
–15%	$63,937	$40.7 million
–10%	$81,551	$51.9 million
–5%	$92,151	$58.6 million
–3%	*$93,567*	*$59.5 million*
0%	$91,829	$58.4 million
5%	$76,222	$48.5 million
10%	$40,504	$25.8 million
15%	($20,608)	($13.1 million)

Notes: Italics indicate highest level of profit.

that the optimal percentage of product returns that maximize firm profits was 13%, or a decrease in product returns by 3% from the current level.

The results of this analysis show that though the current amount of product returns is not at the optimal point, the firm is only 3% away from the optimal amount of product returns to maximize profits and that the optimal amount of product returns is not close to 0%. In addition, Table 7 shows that decreases in product returns beyond 13% decrease profits slowly; at 1%, or 15% below the current amount of product returns, profit is $63,937. However, increases in product returns significantly decrease profits; at 31%, or 15% above the current amount of product returns, profit is –$20,608.

However, the results of this analysis should not be applied directly to a change in the focal firm's product return policy to try to decrease product returns from 16% to 13%. Changing the product return policy is also likely to change customer buying behavior both before purchase and after product return (Nasr-Bechwati and Siegal 2005; Wood 2001). To determine an optimal product return policy, the firm would need to determine how changes in product return policies affect customer purchase behavior. Instead, to reduce product returns to the optimal level, the results of this simulation can provide insights for the firm to implement marketing campaigns to help decrease customer product return behavior. This can be done using the antecedents of product return behavior as levers for increasing each customer's profitability by maximizing the difference between products purchased and products returned.

Implications

The main contribution of this article is in showing that product returns are inevitable but by no means evil. We show this in the following three ways:

1. A customer's product return behavior positively affects his or her future buying behavior, up to a threshold.
2. Including product returns in the analysis of the firm–customer exchange process as an independent and dependent variable increases the accuracy with which we can predict a customer's buying behavior, a customer's product return behavior, and a firm's decision to allocate marketing resources.
3. Allowing for a moderate amount of product returns, given the current return policy by the focal firm of the study (13%), maximizes firm profits.

In addition, the other significant contribution of this article is the use of the SUR Tobit model, which enabled us to model simultaneously a customer's product return and buying behavior and a firm's decision to allocate resources. By modeling the three aspects of the firm–customer exchange process together and accounting for the censored/truncated nature of the data, we can remove any potential biases that may be inherent in the data and/or modeling application.

In some cases, when a customer's return experiences are positive (e.g., a customer can return a product relatively easily and hassle free), this offers the retailer a chance to build the relationship with the customer and reap positive behavioral outcomes. These outcomes can include, but are not limited to, increases in spending/revenue, customers' willingness to pay price premiums, and customers' willingness to refer new customers to the retailer (Zeithaml, Berry, and Parasuraman 1996). These behavioral outcomes all have direct effects on the company's bottom line, whether through increasing customer lifetime value (i.e., increases in spending/revenue and price premiums) or by increasing customer equity by retaining customers who tend to refer additional customers to purchase (Hogan, Lemon, and Libai 2003; Kumar, Petersen, and Leone 2007).

Currently, many retailers do not include product returns as a key part of their customer relationship management strategy and often view product returns as a hassle to the business and a drain on the supply chain. As a result, many firms make efforts to streamline their supply chains to reduce the impact of product returns on the bottom line. However, managers often ignore or try to dissuade customer product return behavior. As we noted previously, this lack of understanding of how product returns affect the exchange process has led managers to make suboptimal decisions in the allocation of marketing resources. However, this problem can be fixed by observing what helps describe a customer's product return behavior and, in turn, how product return behavior affects the customer's future buying behavior. Only then will managers be able to determine the potential impact of the mismanagement of customer product returns on customer buying behavior over time.

When retailers provide an environment for returning products that satisfies customers, regardless of the leniency of the return policy, this can lead the customers to perceive less risk in making purchases (Bower and Maxham 2006). This happens because customers understand the role of the return policy in the evaluation of the product before purchase (Anderson, Hansen, and Simester 2009; Nasr-Bechwati and Siegal 2005). Subsequently, this can lead to higher levels of customer trust and commitment and even to stronger behavioral and attitudinal loyalty (Morgan and Hunt 1994). As a result of stronger attitudinal loyalty, the customer is likely to purchase even more from the firm because he or she is comfortable returning any product that does not fit his or her needs (Reinartz and Kumar 2002).

In addition, there are many other positive consequences of a customer perceiving less risk when building a relationship with a firm that can create additional customer welfare or goodwill. For example, customers who perceive less risk when making purchases can be candidates for cross-buying (Kumar, George, and Pancras 2008) and multichannel shopping (Venkatesan, Kumar, and Ravishanker 2007), both of which have been shown to lead to an incrementally higher customer lifetime value. This research shows that though it likely costs more in the short run for a firm to have a lenient product return policy, in the long run, retailers and managers can use information from each customer's product return behavior as a tool for realizing long-term relationship growth and maximizing each customer's profitability. Thus, managers can actively use information about product returns as a metric for managing customer value and, in turn, can maximize each customer's value to the firm by implementing marketing campaigns targeted at the right customers at the right time.

Limitations and Further Research

Although the results of this study were based on a single firm's lenient product return policy, all managers should not necessarily view leniency as the best return policy. The specific retailer in this study prides itself on product quality and expects that because of its high product quality, customers will return fewer products in total. For some discount retailers, offering products at the lowest price may be the top priority. As a result, if discount firms have a lower product quality, an extremely lenient return policy may cause the number of product returns to increase to a point at which business becomes unprofitable. In such cases, firms may find that an ideal return policy is one that offers some disincentives to return products, such as a restocking fee or a limitation on the number of days after purchase. To help determine the optimal product return policies across different firms, further research should consider data across several different firms with varying product return policies. This will help shed light on optimal return policies for different types of firms (business to consumer versus business to business), different types of industries (e.g., high-tech versus apparel), stores with different characteristics (e.g., catalog versus bricks-and-mortar), and stores that sell across many different product categories (Anderson, Hansen, and Simester 2009).

In addition, our findings suggest that because product returns are positively related (up to a threshold) to future purchase behavior and negatively related (up to a threshold) to the firm's decision to allocate resources, the firm is likely allocating resources suboptimally. However, this study is descriptive in nature, and though its implications to marketing are broad, further research is necessary if a manager wants to use information on buying behavior, product return behavior, and past marketing communications to allocate marketing resources optimally to maximize future customer profitability.

Appendix A
Details on Cube Root Power Transformation

When we augmented the original censored and truncated endogenous variables to estimate the model, the new augmented variable in the linear case was distributed normally. However, when we square this variable, the result is heavily skewed to the right. This occurs because all the values that were previously zero are now negative in the linear case and positive in the squared case. The result is a variable that is significantly right skewed compared with the case in which the original variable is squared. To correct for this problem, we can use a power transformation to improve normality and reduce skewness.

In the case of data that are distributed chi-square (as is the case when the augmented variable is squared), it is common to use a cube root transformation of the given variable to induce normality (Chen and Deo 2004). Thus, after squaring the augmented data, we take the cube root of the value and use the transformed value as an independent variable. We found that this transformation significantly reduced the right skewness of the data.

The parameter estimates we obtain cannot be transformed back in the same way. We need to interpret the results of the transformed variable and use the transformed variable in prediction. In the case of this study, the variable being transformed using a cube root power transformation was distributed chi-square. Thus, if we observe a negative parameter estimate on the transformed variable with a positive parameter estimate on the linear augmented variable, it suggests that a saturation effect is occurring. Because we are not transforming the parameter estimate back to the original variable, the size of the effect is difficult to interpret. However, the sign of the parameter estimate can be interpreted in the same way as the original variable, given that we are taking a cube root of the original variable that was distributed chi-square.

Appendix B

Estimation Algorithm: The SUR Tobit Model

We estimate the latent class SUR Tobit model using an adaptation of the MCECM algorithm as described by Huang (1999). Consider the general case of the SUR Tobit model, in which there are p regressions with n observations:

$$\text{(B1)}\quad y^*_{ij} = X'_{ij}\beta_i + \varepsilon_i,\ 1 \le i \le p,\ 1 \le j \le n,\ \varepsilon_i \sim \text{iid}N_p(0, \Omega)$$

$$y_{ij} = \begin{cases} y^*_{ij} & \text{if } y^*_{ij} > 0 \\ 0 & \text{if } y^*_{ij} \le 0 \end{cases},$$

where in the case of this study,

$$\text{(B2)}\qquad y^*_{ij} = \begin{bmatrix} PR^*_{i,t} \\ Buy^*_{i,t-1\to t} \\ MKTG^*_{i,t-1\to t} \end{bmatrix},$$

$$X_{ij} = \begin{bmatrix} x^{PR} & 0 & 0 \\ 0 & x^{Buy} & 0 \\ 0 & 0 & x^{MKTG} \end{bmatrix},\ \varepsilon_i = \begin{bmatrix} \varepsilon_{PR} \\ \varepsilon_{Buy} \\ \varepsilon_{MKTG} \end{bmatrix}.$$

MCECM Algorithm

1. MCE step. The MCE step, or Monte Carlo expectation step, is used in place of the E step in the expectation-maximization (EM) algorithm. As a result, the Q function from the MCE step for the general case of the SUR Tobit is estimated as the ergodic average:

$$\text{(B3)} \qquad Q\left[(\beta,\ \Omega),(\beta^{(i)},\ \Omega^{(i)})\right] = -\frac{np}{2}\ln(2\pi) - \frac{n}{2}\ln\left|\Omega\right|$$

$$+\frac{1}{N}\sum_{k=1}^{N}\left[-\frac{1}{2}\sum_{j=1}^{n}(y^*_{ij} - X_j\beta)'\Omega^{-1}(y^*_{ij} - X_j\beta)\right],$$

where values of y_{ij} that equal 0 are replaced by values drawn from a truncated normal distribution with mean $X_j\beta$ and variance Ω [$TN_{(-\infty,\ 0)}(X_j\beta,\ \Omega)$]. This Q function will converge to its true value as N approaches infinity.

2. CM step. The CM step, or conditional maximization step, is performed by the maximization of β given Ω and of Ω given β. This is done by iteratively updating the values of β and Ω, such that

$$\text{(B4)} \qquad \beta^{(i+1)} = \left(\sum_{j=1}^{n}X_j'\Omega^{-1}X_j\right)^{-1}\left(\sum_{j=1}^{n}X_j'\Omega^{-1}\overline{y}_j\right),$$

$$\overline{y} = \frac{1}{N}\sum_{k=1}^{N}y_j^{*(k)},$$

$$\text{(B5)} \qquad \Omega^{(i+1)} = \frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{n}\left(y_j^{*(k)} - X_j\beta\right)\left(y_j^{*(k)} - X_j\beta\right)'.$$

Appendix C
Latent Class Segmentation

The latent class segmentation of the customers into m homogeneous segments can be carried out as follows: We assume that there are somewhere between 1 and M homogeneous segments, where M is the number of customers or households in the data set. Each segment will have the following relative size:

$$\text{(C1)} \qquad f_m = \frac{\exp(\lambda_m)}{\sum\exp(\lambda_m)},$$

where f_m is the size of segment m as a percentage of total population size.

The likelihood of the latent class segmentation model can be computed as follows:

$$\text{(C2)} \qquad L(Q) = \sum_m\left[\frac{\exp(\lambda_m)L(Q|m)}{\sum_m\exp(\lambda_m)}\right],$$

where L(Q|m) is the expectation of the Q function given that the segment membership is m.

We carry out this latent class segmentation of customers, hypothesizing that there are more than one latent segment of customers in the data. We do this by setting the number of segments to different numbers (1, …, m) and then determining how many latent segments are uncovered. We attempted a one-, two-, three-, and four-segment solution. The results we obtained are as follows:

Results from the Latent Class Analysis

Number of Segments	Segment Size	–2 × Log-Likelihood	CAIC
1	100%	16,349	**16,676**
2	95% and 5%	16,159	16,813
3	80%, 13%, and 7%	15,996	16,997
4	68%, 14%, 11%, and 7%	15,761	17,069

We chose the model (noted in bold font) with the lowest CAIC (16,676) for the optimal number of segments (Jedidi, Ramaswami, and DeSarbo 1993). Thus, we select one segment as the optimal number of segments for this latent class analysis. The CAIC is an alternative measure to the AIC that corrects for the overestimation bias in AIC by penalizing for overparameterization. It is defined as follows:

$$CAIC_m = -2\times\ln[L(Q|m)] + N_m(\ln I + 1),$$

where

L(Q|m) = the likelihood of the model given segment m,
N_m = the effective number of parameters estimated in an m-class solution, and
I = the number of observations in the sample.

A one-segment solution means that there is no significant benefit to segmenting customers into multiple latent segments. However, a one-segment solution does not mean that there is no variation between segments. It means only that the additional variance explained by dividing customers into multiple segments is outweighed by the reduction in parsimony from the use of too many parameters. In addition, it suggests that the variables used in the three models explained much of the heterogeneity among customers.

The parameter estimates for each of the four latent class estimations (one, two, three, and four segments) showed only slight differences between each segment in each of the models, both in magnitude and significance. (Parameter estimates for the two-, three-, and four-segment solutions are available on request.) However, in almost no cases did we observe the signs of the parameter estimates change. As a result, the slight, but not significant, increase in variance explained when each additional segment is added leads to the one-segment solution having the lowest CAIC.

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