The Impact of Online Product Reviews on Product Returns and Net Sales

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Abstract

Although many researchers in Information Systems and Marketing have studied the effect of product reviews on sales, few have looked at their effect on return of such purchases, i.e. on the net sales. We motivate the idea that product reviews could affect the quality of purchase decisions, hence the probability of the eventual return of the purchased products. To explore this we obtain a transaction level dataset from a multi-channel multi-brand specialty retailer operating in North America. We study the impact of product, customer, marketing, and customer-generated review variables on the probability of a purchase being returned. We find that the availability of online product reviews is associated with a lower probability of return after controlling for customer, product and channel related factors. The findings form the basis of our current work on modeling the purchase and return activities in terms of uncertainty around customer's anticipated utility and the latent cost of return.

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Draft of Work-In-Progress

Introduction

A long literature in information systems and marketing has established the influence of product reviews on sales. However, most sales are not final and customers have the right to return products. Product returns are extremely costly for both manufacturers and retailers with lost revenues representing over $ 100 billion, or an average loss of 3.8% per firm (Blanchard 2005).[1] High returns pose a particular problem for online retailers with return rates as high as 50% (Martinez 2009), with certain categories such as fashion goods experiencing even higher return rates.

A complete understanding of the impact of product reviews on manufacturer and retailer's sales and profits must, thus, also examine how they influence product returns and final sales (i.e. sales, net of returns). Despite industry claims that product reviews lead to fewer returns,[2] to the best of our knowledge, this question has not been previously addressed in academic research. We fill this gap by offering what we believe is the first academic study of the impact of product reviews on product returns and final sales.

Related Work

There are two streams of literature that are relevant to our research focus. The first stream examines product reviews whereas the second investigates product returns.

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[1] These costs include the costs of processing a returned product such as unpacking, checking, repacking and restocking as well as the refund costs. Frequently additional costs, such as shipping costs and costs associated with products returned in used condition, can occur.

[2] See, for example, the marketing literature of leading ratings and reviews solution provider BazaarVoice (http://www.bazaarvoice.com/industries/) and sponsored case studies such as "PETCO Slashes Return Rates with Bazaarvoice Ratings & Reviews" (http://www.businesswire.com/news/home/20070626005416/en/PETCO-Slashes-Return-Rates-Bazaarvoice-Ratings-Reviews)

Over the past 10 years, the literatures of information systems and marketing have devoted a lot of attention to the study of online product reviews. Several studies have examined the relationship between online reviews and sales. For example, in an online experiment, Senecal and Nantel (2004) find that participants who consulted product recommendations selected these products twice as often as those who did not consult recommendations. Chevalier and Mayzlin (2006) find that online consumer ratings significantly influence product sales in the book market and that customers actually read review text in addition to the reviews' summary statistics. More recently, Luca (2012) finds that a one star increase in a restaurant's Yelp rating led to 5-9% increase in revenues. Other studies have looked more deeply into aspects of this question, studying, for example, the differential impact of reviews in different product categories and for different consumers (Zhu and Zhang 2010), the impact of review text (Archak et al. 2011) and the impact of reviewer identity disclosure (Forman et al. 2008).

There is, similarly, a large marketing literature on product returns. Return policies and marketing actions of the firm have been shown to be used as information influencing the pre-purchase phase (Petersen and Kumar 2009; Shah et al. 2012). Research shows that many consumers value more lenient return policies in the purchase consideration phase and returns have been shown to increase overall sales (Wood 2001). At the time of purchase, there are a number of marketing mix decisions and product specific variables that have been shown to affect returns. For example, Hess and Mayhew (1997) suggest that return rates vary across product categories with some product categories having return rates as high as 25% (e.g., shoes) while others have virtually no returns (e.g., socks). From a marketing mix perspective, products purchased at lower prices (Anderson et al. 2009) and while on promotion (Petersen and Kumar 2009) are less likely to be returned due to the perceived value in such purchase situations. Within a multi-channel context, retailers will need to consider cross-channel impact of purchases of multi-channel shopping e.g., purchases in an offline store that might be returned in an online store (Ofek, Katona and Sarvary 2011). Collectively, these papers suggest that when drawing inferences on expected demand, it is important to consider both customer purchase behavior as well as return behavior to allow for an assessment of the net impact on revenues (Anderson et al. 2009).

Despite the interest in both topics, we are unaware of any study that looks into the impact of online reviews on product returns.

Data Description

To investigate this effect we obtained a transaction level dataset from a North American Specialty Retailer[3]. This is a specialty retailer, like GAP, whose products are sold only through the company owned online and offline stores. The data was collected over July 2010 to June 2012.

The dataset consists of information about product, customers, transactions and promotions run by the firm. The product information includes category, description, and ratings & reviews received. Additional information about the individual product-reviews such as date of review, how often the readers found the review to be helpful and whether an experienced reviewer wrote it is also collected. The customer information includes age, gender, zip code, and distances to the nearest store for each brand. In addition, we have record of the products they browsed, online searches they performed, and product-reviews they wrote. All the purchases and returns made by the customers in the dataset, either offline or online, are recorded as well. Such transaction data include the items purchased, price paid, promotions applied, if any, the purchase location, and whether and how the purchase was returned. Each promotional email or catalog sent to each of these customers was recorded with timestamps as well.

Brand	A	B	C
# of customers (partially overlapping sets, total of 42K)	24K	12K	27K
# of products	29K	6K	32K
# of products with reviews	17K	6K	23K
# of reviews	129K	32K	115K
Average ratings on the products	4.21	4.24	4.07
# of product views	3.4M	1.1M	3.5M
# of searches	39K	34K	133K
# of purchases	417K	70K	303K
# of returns	80K	12K	34K
# of catalogs mailed	293K	251K	254K
# of emails sent	3.4M	1.8M	5.4M

Table 1 Data description

The retailer operates three different brands. The first sells women's apparel, accessories, and decorative home items (Brand A). The second focuses on trendy clothing items for women in their

[3] We are grateful to Wharton Customer Analytics Initiative for making this dataset available (http://www.wharton.upenn.edu/wcai/)

20s (Brand B). The third is the flagship brand of the retailer that sells trendy apparels and accessories for men & women as well as some home furniture (Brand C). The three brands target three different segments and are managed largely independently. The descriptive statistics of the three brands are presented in Table 1.

Model of Returned Purchases and Variables

We hypothesize that information from product reviews reduce uncertainty resulting in better purchase decisions and a lower probability of return. In addition, there is a cost associated with returning a product that may be higher for certain products and customers—making returns less likely for them.

To test these hypotheses we build a transaction level logistic regression model. The set of purchases by the customers in our dataset form the complete set of events. If a purchase was returned the outcome of the event, which is the dependent variable, is set to 1, else it is set to 0.

Six sets of independent variables are postulated to affect the probability of return. The variables are computed for each brand and for each transaction when appropriate. They are defined as follows:

1. **Product characteristics**: Certain types of products are systematically more likely to be returned than other types. E.g., we may expect bulkier items to be returned less often than smaller items due to the difficulty involved. Similarly cheaper items might be returned less often because the value might not be worth the effort associated with the return. Hence, the two variables included are:
    a. Product Category: one of Accessories, Clothes, Furniture, Home, and Misc
    b. Product Expensiveness (measured as price paid)
2. **Product review variables**: More available information about the products from customer reviews should lead to better purchase decision by customers, lowering the probability of return. To test this we include a set of variables capturing different aspects of the product reviews that were available at the time of purchase. They are:
    a. Volume of reviews
    b. Average rating
    c. Standard deviation of the ratings—to capture the disagreement about the product quality

d. Helpful reviews: This variable contains the total number of helpful reviews a product has. A review is coded as helpful if it has more votes from readers indicating that it was helpful than votes indicating that it was unhelpful.
e. Reviews from top reviewers: The reviewers who have contributed the most are given an online badge (e.g., top 250 reviewer or top 1000 reviewer) and their status is displayed next to the reviews they write. This variable contains the number of reviews the product has from the top reviewers.

3. **Customer characteristics**: These are control variables for effect of demographic attributes on the probability of returns.
   a. Age: Converted to a binary variable split on the median age of 24
   b. Gender: Male=0, Female=1
   c. Distance: The distance of the customer from the nearest store in miles
   d. Frequency: Number of transactions conducted by the customer per year
   e. Revenue: $ spent by the customer per year
   f. Multichannel: The fraction of the purchases made by the customer in online channel is computed. A dummy variable is constructed out of this fraction that indicates whether a customer is primarily offline shopper, a multi-channel shopper, or primarily online shopper.
   g. Customer specific random intercept: To control for the individual customer's propensity for returning the purchased products, we include a customer-specific random intercept.
4. **Customer activity**: Customers who conduct active research prior to purchase might have a lower purchase probability than the customers who don't. To measure this effect we computed the following variables based on the consumer activities in the 2 weeks prior to the purchase
   a. Number of products the consumer browsed
   b. Number of searches the consumer conducted
5. **Marketing contacts**: The consumer is encouraged to shop through catalogs and marketing emails by the firm. To the extent they accurately inform the customers about the products, they can help them take a better purchase decision. However, if they do not they can lead to purchases that would not have happened naturally. It may result in inferior matches and lead to higher rate of returns. To study this effect we use the following two variables based on the marketing contacts with the customer in the two weeks leading up to the purchase:
   a. Number of catalogs delivered
   b. Number of E-mails delivered

6. **Context variables**: The context of purchase can have an important effect on the probability of return. The purchases made in stores are likely to be based on more information than purchases made online. Hence, we might expect a lower rate of return for those purchases. Similarly, customers often purchase more than one items at a time with the intention of keeping only one. We use the following two contextual variables:
    a. Channel of purchase: online = 0, in-store = 1
    b. Whether a promotion was applied
    c. Recency: -ve of time since last purchase measured in months

The results from the three logistic regression equations are shown in Table 2.

Discussion

The number of reviews available at the time of purchase has a significant –ve effect on the probability of return. This supports the hypothesis that the more information customers have at the time of purchase, better will be the fit of the purchase decision with customer preferences reflected in a lower return probability. This is observed after controlling for the average product ratings, which is a proxy for product quality. A further interesting point is that, as the standard deviation of the ratings increase, so does the probability of return. This suggests that a lack of clear information about the product quality can lead to less effective purchase decisions.

The purchases where a promotion was applied have a higher probability of return. In addition, if the customer has received catalogs and email marketing in the two weeks before the purchase, there is a higher probability of the purchase being returned. This indicates the possibility that many of such purchases occurring due to promotions might not have happened otherwise. On an average these might reflect inferior matches between customers and products than those that happen naturally when there is no promotion.

A customer's amount of search and browsing has a positive association with the probability of return. This is counter to what we hypothesized. This can be explained by observing that the consumers might gather more information before purchases for which there is more uncertainty. This uncertainty about the product fit may not be mitigated through the available online information. In our ongoing work we will explore this interesting finding deeper.

Returns are more likely for expensive products, less likely for the distant customers, and less likely for furniture. This supports the idea of a latent cost of return that is higher for distant customers, higher for heavier items such as furniture. In addition, for cheaper products it is more likely that the value of the product is lower than the cost to return it—resulting in a lower probability of return. To contrast with this finding: clothes have a higher probability of return, presumably because there is a high degree of uncertainty around the fit and they are relatively easier to return than, say, furniture.

		Brand A		Brand B		Brand C	
	(Intercept)	-2.4130	***	-2.8090	***	-3.2000	***
Transaction Context	In-store purchase	-0.5907	***	-0.6857	***	-0.6630	***
	Promo?	0.1080	**	0.2072	.	-0.0298	
Product Characteristics	Price	0.0080	***	0.0060	***	0.0165	***
	Accessories			*Reference Category*			
	Clothes	0.3797	***	0.6459	***	0.3955	***
	Furniture	-3.8030	***				
	Home	-0.6047	***			-0.6973	***
	Misc	0.3329	**			-0.7672	
Product Reviews	log(num reviews)	-0.0647	***	-0.0993	***	-0.0693	***
	Avg_rating	-0.1642	***	-0.1040	*	-0.1274	***
	sdev_rating	0.0710	**	0.0627		0.0669	*
	Fraction of helpful reviews	0.1607	***	-0.0303		0.0526	
	Fraction of reviews from top reviewers	0.0853	**	-0.0421		-0.1356	*
Customer Activities	# of searches	-0.0372	.	0.0249		-0.0273	
	# of products browsed	0.0583	***	0.0892	***	0.1276	***
	Recency	0.0000	***	0.0000	*	0.0000	
Customer Characteristics	Age>24	0.5403	***	0.2816	*	0.1854	***
	Male?	-0.3024	***	-0.5095	*	-0.3103	***
	Distance from store (miles)	-0.0009	***	-0.0003		-0.0009	**
	Frequency of shopping (annual)	0.0098	***	0.0027	**	0.0105	***
	Revenue spent in $1000s (annual)	-0.2683	***	-0.1048	***	-0.3295	***
	1/3 to 2/3 purchases made online	-0.3750	***	-0.3331	**	-0.1209	.
	2/3 to all purchases made online	-0.5752	***	-0.3349	*	-0.3227	***

Table 2 Effects of product reviews, product characteristics, and customer activities on probability of return. Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Purchases in a retail stores have a significantly lower probability of being returned. This is not surprising since a customer can physically examine the product and can have much more information about the product.

All these discussed findings are consistent across the three brands. This suggests that the observed phenomena are likely to generalize well.

Model of Purchases

The results in Table 2 are of returns based on purchase events that already took place. One of the limitation of this setup is that although it can inform us about the effects of different factors on the probability of a purchase being returned, it does not inform us about the effect of these factors on the original purchase itself. E.g., the results suggest that the more reviews a product has the lower is the probability of it being returned, once it is purchased. However, do more reviews reduce the probability of purchase in the first place?

To study the effect of these factors on the purchase event itself, we build a second logistic regression model where each event corresponds to a unique product browsed by a customer during the first 18 months of the data collection period. The outcome of the event was set to 1 if the browsed product was purchased during the entire 24 months of observation period. Else it was set to 0. The set of explanatory variables were same as before, except the variables representing the context of purchase such as promotions applied and channel of purchase are not applicable for the products browsed by the customer. Instead, we included another variable representing the number of times the customer browsed the product, to control for the inherent interest of the customer in the product. The results from this analysis are shown in Table 3.

		Brand A		Brand B		Brand C	
	(Intercept)	-5.3329	***	-5.7257	***	-5.5076	***
Transaction Context	# of times browsed	0.2186	***	0.1498	***	0.2261	***
Product Characteristics	Accessories			*Reference Category*			
	Clothes	0.1127	***	-0.0227		0.0309	
	Home	0.0618					
	Misc	0.0037					
Product Reviews	log(num reviews)	0.1360	***	0.1826	***	0.1189	***
	Avg_rating	0.2840	***	0.2536	***	0.2205	***
	sdev_rating	0.0053		-0.0436		-0.0789	***
	Fraction of helpful reviews	0.0695	**	0.2991	***	0.3507	***
	Fraction of reviews from top reviewers	0.2994	***	0.1415	**	0.1747	***
Customer Activities	# of searches	0.3112	***	0.1680	***	0.3113	***
	# of products browsed	-0.2108	***	-0.1116	***	-0.1640	***
	Recency	-0.0025	***	-0.0024	***	-0.0039	***

	Age>24	0.4948	***	0.3787	***	0.2703	***
	Male?	-0.2102	*	-0.3044	*	0.1512	*
	Distance from store (miles)	-0.0002		-0.0003		-0.0002	
Customer Characteristics	Frequency of shopping (annual)	-0.0004		-0.0029	**	0.0071	***
	Revenue spent in $1000s (annual)	0.1724	***	0.1532	***	0.0495	
	1/3 to 2/3 purchases made online	-0.1225	**	0.3555	***	0.1828	***
	2/3 to all purchases made online	-0.4368	***	0.2933	***	0.0061	

Table 3 Effects of product reviews, product characteristics, and customer activities on probability of purchase. Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Discussion

We find that additional product reviews are not only associated with the reduced probability of return, they are also associated with an increased probability of purchase of the item. This is an additional effect after controlling for the average ratings, which has a positive effect as expected.

The presence of reviews that are perceived helpful or reviews that are from top reviewers has a positive effect on the purchase of the browsed product. This observation seems to suggest that reviews that are perceived useful lead to a higher probability of purchase, but, according to the results in Table 2, not necessarily an improved quality of purchase decision. The products with more such reviews have a higher probability of being returned.

Amount of browsing of products is negatively associated with the purchase of a specific product, whereas the amount of searching is positively associated with purchase. These two activities represent two different steps on the path to purchase. When a customer actively searches for a product using the available search engine, she is likely to be further along the path towards the purchase.

These discussed findings are also consistent across the three brands, once again suggesting that the observed phenomena are likely to generalize well.

Summary

The effect of online reviews on sales has been widely studied. However, their effect on product returns has not been explored in the literature. Using a multi-brand multi-channel longitudinal dataset encompassing various customer touch points, we study the effect of online product reviews on the return of a purchased product for the first time. We find that there is a significant –ve effect of number of product reviews available at the time of purchase on the eventual return of the purchased product. This effect is found to be significant after controlling for a number of product and customer specific factors. The effect was consistent across three different brands, adding support to the generalizability of these results.

We also find that offline purchases are less likely to be returned than online purchases. This along with the –ve effect of volume of reviews, adds support to the idea that more information at the time of purchase is associated with lower return.

We find evidence in support of latent cost associated with returning a product that increases with distance of the customer from the store and the bulkiness of the item. This makes return of certain products, especially low value items, unattractive.

Ongoing Work

We are currently in the process of extending our initial model and results in a number of directions.

Building on the evidence of latent cost of return and the value of information at the time of purchase, we are developing a model to more directly study how different customer and product characteristics outlined in this paper affect the quality of purchase decision.

We would like to understand how the text of online reviews influence product returns. We are, therefore, in the process of conducting text mining on the corpus of review texts. For example, we classify reviews as objective or subjective and examine whether the distribution of objective vs. subjective reviews for different products has an impact on returns. In addition, in the spirit of Archak et al. (2011) we will explore whether the presence of certain topics or keywords in the text of reviews affects returns in a statistically significant manner.

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