

# An Empirical Investigation of the Effects of Product-Oriented Web Technologies on Product Returns

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Last revised: February 2012

## Abstract

Internet retailers have been making significant investments in advanced technologies, e.g., zoom, alternative photos, and color swatch, that are capable of providing detailed product-oriented information and, thereby, mitigating the lack of “touch-and-feel,” which, in turn, is expected to lower product returns. However, a clear understanding of the impact of these technologies on product returns is still lacking. This study attempts to fill this gap by using several econometric models to unravel the relationship between product-oriented technology usage and product returns. Our unique and rich dataset allows us to measure technology usage at the product level for each consumer. The results show that zoom usage has a negative coefficient, suggesting that a higher use of the zoom technology leads to fewer returns. Interestingly, we find that the use of alternative photos increases the likelihood of returns. Perhaps more importantly, its use has a negative effect on net sales. Color swatch, on the other hand, does not seem to have any impact on returns. Thus, our findings show that different technologies have different effects on product returns. We provide explanations for these findings based on the extant literature. We also conduct a number of tests to ensure the robustness of the results.

**Key Words:** online shopping; product returns; product-oriented technologies; econometric models.

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## 1. Introduction

“We used to produce one picture per product. Now we need five or six shots, reflecting different backgrounds, angles, and perspectives. Our customers want to see more photos of what they are planning to buy.”

Jim Klar, Multimedia Marketing, MonsterCable.com (Bock 2006)

A key issue that hampers the growth of Internet commerce is the difficulty of providing accurate and detailed product information to consumers. An online consumer survey reports that sixty-seven percent of consumers who visited an online store intending to purchase left the site because the online store did not give them enough product information (Internet Retailer Magazine 2006). The difficulty of conveying product information to consumers leads to not only lost sales opportunities but also higher likelihood of costly product returns (Ofek et al. 2010).

To mitigate the lack of “touch-and-feel” and close inspection in Internet retailing, Internet retailers have been making significant investments recently in advanced technologies that are capable of providing more detailed product information to consumers. Technologies such as zoom, color swatch, and alternative photos have become Internet retailers’ priorities as they try to improve consumers’ shopping experience (Forrester Research 2009). More specifically, zoom allows a consumer to inspect finer details of the focal product; alternative photos allow a consumer to look at the product or a model wearing the product from different angles; and color swatch enables a consumer to change the color of the product to other available colors for better visualization. Investments in these product-oriented technologies are expected to eventually lead to improvements in providing information to consumers and reductions in product returns (Young 2007, Bustos 2009).<sup>1</sup> It is worth noting that product returns are a very significant problem for most retailers. Returns cost U.S. manufacturers and retailers almost \$100 billion per year because of product depreciation and reverse logistics (Blanchard 2005, 2007).<sup>2</sup> Return rates could be as high as 25% for some retailers (Hess and Meyhew 1997). High return rates could be a particularly acute problem for Internet retailers (Hammond and Kohler 2001) because of the greater difficulty of communicating accurate product information to consumers on the Internet.

Despite the importance of the product return problem and the considerable investment in product-oriented technologies (Walker et al. 2010), academics and practitioners alike have very limited

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<sup>1</sup> In addition to these product-oriented technologies, Internet retailers also use navigational technologies (e.g., search and recommendation). These latter technologies help consumers find a product. While they may have an impact on sales (see, for example, De et. al 2010), they are not likely to influence returns because they do not play a role in forming consumers’ pre-purchase expectations.

<sup>2</sup> To mitigate the problem of returns, retailers have adopted various strategies aimed at minimizing return rates. Such strategies include offering strict return policies, charging restocking fees, and making consumers responsible for the cost of return shipping.

knowledge about how consumers use these technologies (i.e., zoom, alternative photos, and color swatch) and how the use of these technologies influences product returns. The lack of research on this topic could be traced to the difficulty of obtaining appropriate data for such studies – it is difficult to measure online consumers’ information acquisition behaviors. An Internet retailer’s server logs often contain such information, but it is not easy to extract relevant information from millions of lines of server logs. In addition, it is challenging to match the technology usage measures with transaction data that contains product purchase and return information.

This paper advances the existing literature in at least two key ways. First, our unique data set allows us to measure online consumers’ information acquisition behaviors and relate such measures to their actual product returns. This adds to the existing literature that has been using data collected from lab experiments and surveys to study consumers’ use of web technologies and consumers’ product returns (e.g., Jiang and Benbasat 2004, 2007, Hong and Pavlou 2010). Second, we introduce to this literature the concept of factual and impression-based information, a concept first introduced by Holbrook (1978) and later widely used in the literature on the effect of advertising (see Shimp and Preston 1981 for a literature review). Most existing studies examining consumers’ use of web technologies and consumers’ product returns have assumed that consumers obtain only objective, factual information; therefore, more product information leads to less product uncertainty and more realistic product expectations, which translate to fewer returns. In contrast, we propose that at least a part of the product information gained by consumers could be based on their subjective, emotional impressions or feelings toward the product. Since such impression-based or evaluative information has proven to inflate consumers’ beliefs and expectations of products (Burke et al. 1988), our paper raises the possibility that consumers who gain a high level of impression-based information may, in fact, return more.

The research setting of our study is the retailing of clothing products on the Internet, an industry that is currently undergoing rapid adoption of advanced product-oriented technologies. The clothing product category is also a category in which both factual information and impression-based information play key roles in consumers’ decision making (Hammond and Kohler 2001). We have obtained data from a women’s clothing retailer that has implemented all of the aforementioned product-oriented technologies, namely, zoom, alternative photos, and color swatch. We use a relative scale to characterize how each of these technologies draws consumers’ attention toward different types of product information along the lines of Holbrook (1978) and Holbrook and Batra (1987). Based on two independent judges’ evaluations using this scale, we find that, in our research setting, the zoom capability, which enables consumers to get a closer look of any part of the product, provides mostly factual information; the alternative photo technology, which allows consumers to see pictures of a beautiful model wearing the

focal product, from different angles, often in a scenic environment, conveys primarily impression-based information; and the color swatch technology communicates both factual information (a more vivid depiction of the product color) and impression-based information (visualizing how the focal product in a certain color would look on a beautiful model in a scenic environment), although the latter type of information could be more prevalent. We then build testable hypotheses based on this characterization.

This paper uses several econometric models to empirically investigate the relationship between product-oriented technology usage and product returns. Our unique and rich dataset allows us to estimate various panel data models, and conduct an array of robustness checks to ensure the reliability of our empirical findings. The results show that zoom usage has a negative and weakly significant coefficient, suggesting that a higher use of the zoom technology leads to fewer returns. We also find that the use of the alternative photo technology increases the likelihood of returns. Color swatch, on the other hand, does not seem to have a significant impact on product returns. In summary, our findings indicate that these different technologies have different effects on product returns, depending on how each technology conveys factual or impression-based information to consumers.

Our study makes several notable contributions. Recently, there have been a few studies that examine the effect of technology usage on sales (e.g., De et al. 2010). However, to the best of our knowledge, no one has yet studied the relationship between web technology use and returns. Moreover, unlike the previous studies on product returns, which use lab experiments and survey data, we use actual transaction data. Also, we have been able to analyze the phenomena at a finer level than before – at the product level for each consumer. More importantly, this is the first empirical study to examine the relationship between product-oriented technology usage and product returns. The paper deepens our understanding of the different forms of this technology (namely, zoom, alternative photos, and color swatch) and the ways they affect product returns.

The results of this research have important economic and managerial implications. They will aid Internet retailers in understanding the effects of product-oriented technologies on returns, a factor that greatly affects their profitability. In contrast with navigational technologies (e.g., search and recommendation systems), product-oriented technologies (i.e., zoom, alternative photos, and color swatch) may incur significant ongoing costs because, for example, the addition of a new product would require taking professional pictures in different settings. Consequently, the insights obtained from this paper are likely to be quite useful when Internet retailers decide whether and how they should invest in developing and maintaining such technologies. For instance, our findings suggest that the alternative photo technology could lead to more product returns. Even after the possible changes in sales are considered, this technology could generate a non-desirable outcome. Thus, firms should be careful about

which pictures to be included in the set of alternative photos so that consumers do not form unrealistic expectations regarding this product. In fact, some companies have already started paying attention to this phenomenon. With Amazon as a trend setter in this respect, companies like Wal-Mart, Urban Outfitters, Zales, and even Petco now allow consumers to post their own pictures of the product (Bryan 2011), rather than keeping only professionally produced pictures in an artificial setting.

The rest of the paper proceeds as follows. Section 2 presents a brief literature review, followed by the development of propositions and testable hypotheses. Section 3 describes our research design and data. We outline the empirical models and present the results in section 4, and provide a number of robustness checks and additional analyses in section 5. Finally, the paper concludes with a summary of the results and important insights in section 6.

## **2. Literature Review and Theoretical Background**

### *2.1. Literature Review*

There are only a few papers that have empirically studied actual product returns made by consumers, rather than simply considering the intention of return. Most of these papers focus on the impact of varying return policies (e.g., Wood 2001). More recently, Petersen and Kumar (2009) examine the role of returns in the relationship between consumers and a firm, and identify several factors that explain consumers' return behaviors. Anderson et al. (2009) measure the value of the return option to consumers and demonstrate the effect of different return policies on firm profits. In contrast, our paper is an attempt to empirically examine the relationship between technology usage and returns. De et al. (2010) study the impact of search and recommendation technologies on online sales; they do not, however, consider product-oriented technology usage, nor do they study returns.

This research is also related to the existing literature on consumer satisfaction because returning a purchased product is typically an outcome of a consumer's dissatisfaction with the purchased product (Engel et al. 1995). This literature suggests that the confirmation or disconfirmation of pre-purchase expectations drives consumer satisfaction or dissatisfaction (e.g., Oliver 1980, 1997, Cadotte et al. 1987). In particular, when the perceived quality (or performance) after a consumer receives the product matches her pre-purchase expectation regarding the product, her expectation is confirmed and she becomes satisfied with the purchase. On the other hand, if the perceived quality turns out to be lower than the expectation, then it disconfirms the expectation, which, in turn, leads to dissatisfaction. Hence, the primary stimulant of product returns, i.e., dissatisfaction, basically represents the degree of disparity between the expectation and perceived product quality (Anderson 1973).

Extensive research on consumer satisfaction concludes that the perceived product quality can be positively or negatively influenced by the pre-purchase expectation (e.g., Anderson 1973, Hoch and Young-Won 1986). If this influence is positive, i.e., if the post-purchase product quality judgment moves toward the expectation, then it is called “assimilation”. In general, the assimilation theory posits that if the gap between the expectation and perceived product quality is small enough to fall within a consumer's “latitude of acceptance,” then the perceived quality will tend to move closer to the expectation, i.e., it will converge toward the expectation (Sherif and Hovland 1961). Conversely, if the gap is outside the latitude of acceptance, then the consumer tends to amplify the difference between the expectation and perceived product quality, i.e., the perceived quality diverges further from the expectation, which is known as “contrast” (Anderson 1973).

Our research also draws upon the economics and marketing literatures on the role of product information in influencing consumer behavior. These literatures have shown that consumers need to acquire product information before they can evaluate alternatives and make purchases, and that product information acquired by consumers can have a great impact on their purchase decisions as well as post-purchase outcomes such as satisfaction or dissatisfaction (Engel et al. 1995, Kotler 2002). There is a long stream of research on different types of product information and how product information influences consumer beliefs. An important distinction made by this research is the difference between factual information and impression-based (or evaluative) information, tracing back to Holbrook (1978). This stream of research has found that these two types of product information can influence consumers’ pre-purchase beliefs and expectations in different ways (e.g., Holbrook 1978, Shimp and Preston 1981). Finally, there are several papers in the information systems literature that have studied product information or product uncertainty in online shopping. The inability for consumers to closely inspect or “touch-and-feel” products in an Internet shopping environment limits the amount of product information available to them and increases the uncertainty or risk (Jarvenpaa and Todd 1997). Jiang and Benbasat (2004, 2007) expose student subjects to different product presentation formats and study the resulting change in consumers’ attitude toward products. Hong and Pavlou (2010) conceptualize three dimensions of product uncertainty – especially, fit uncertainty, which matches consumers’ needs with product characteristics – and examine how different types of product pictures can change product uncertainty felt by consumers. Our paper differs from these studies because, among other things, it uses real consumers’ browsing and transaction data.

Having reviewed the related literatures on consumer satisfaction and on the role of product information in changing consumer behavior, we develop the following propositions based on these existing theories.

## 2.2. Propositions

The economics and marketing literatures on consumer behavior have shown that consumer decision process can be divided into five stages: need recognition, information search, alternative evaluation, purchase, and outcome (Engel et al. 1995, Kotler 2002). During the “information search” stage, consumers first try to recall their prior direct experience with the product; they then acquire additional information from external sources such as TV and print advertising, in-store display, package labels, and salespeople. Product information acquired by consumers can have a great impact on their purchase decisions as well as post-purchase outcomes such as satisfaction or dissatisfaction (Engel et al. 1995).

As mentioned earlier, Holbrook (1978) makes an important distinction between two types of product information: factual information and impression-based (or evaluative) information. He defines factual information as “logical, objectively verifiable descriptions of tangible product features” and impression-based (or evaluative) information as “emotional, subjective, impressions of intangible aspects of the product”. Such a distinction is similar to the distinction between “facts” and “feelings” used in advertising (Olney et al. 1991), and between search and experience qualities described by Nelson (1970, 1974).

Factual information often has a significant impact on consumers’ beliefs. The literature on deceptive advertising has found that this type of information makes consumers less vulnerable to misleading advertising claims (Aaker 1974, Gardner 1975). Thus, when a consumer gains more factual information about a product, her pre-purchase expectation about the product will be more realistic, which means that the gap between the pre-purchase expectation and post-purchase perceived quality will become smaller (Anderson and Sullivan 1993). If this gap becomes small enough to be within the latitude of acceptance of the consumer, then the assimilation effect will set in (Anderson 1973, Anderson and Sullivan 1993). In other words, the perceived quality will now move toward the expectation, reducing the gap even further. Because of this small gap, the consumer will more likely be satisfied, which, in turn, will reduce the reason for her returning the product. This observation is captured in the following proposition.

**Proposition 1:** *Factual information has a negative effect on product returns.*

Impression-based information often alters consumers’ beliefs via an implication process in which consumers try to infer implied meanings from the information they are exposed to (Preston 1967, Harris 1977, Shimp 1978). Because impression-based information is typically ambiguous and hard to verify, such an implication process may lead consumers to believe something that is neither explicitly stated nor

logically implied (Shimp 1978). Consequently, such information may help consumers form an unrealistically high expectation regarding a product (Burke et al. 1988). The expectation may be inflated even more because of another effect: when consumers are presented with multiple positive images, their overall impression is often guided by the most positive of these images (Chowdhury et al. 2008). Because of this inflated expectation, the gap between the pre-purchase expectation and post-purchase perceived quality is likely to be large when a consumer obtains primarily impression-based information. In fact, following the contrast effect (Anderson 1973), the perceived quality may now move away further from the expectation, making the gap even larger. Because of this large gap, the consumer is likely to be dissatisfied with the product after purchase, which would often result in a return. Therefore, we conclude that the impression-based information obtained by a consumer about a product is likely to have a positive effect on the likelihood of her returning the product. This leads us to the following proposition.

**Proposition 2:** *Impression-based information has a positive effect on product returns.*

We note that the papers that have studied the effects of product presentation technologies in online shopping so far only examine the role of factual information (e.g., Jiang and Benbasat 2004, 2007). Our paper extends this literature by bringing in the possibility of impression-based information. Next, we link these different types of product information to consumers' use of various product-oriented technologies in the context of our study and arrive at testable hypotheses.

### *2.3. Testable Hypotheses*

To arrive at testable hypotheses, we first characterize how each technology helps consumers obtain different types of product information. Following prior research that characterizes the type of product information gained by consumers and measure the effect of product information on consumers' beliefs (e.g., Holbrook 1978 and Holbrook and Batra 1987), we have hired two judges and assigned them the task of rating the nature of product information on a seven-point scale ranging from "highly factual" to "highly impression-based". A rating of one means that the information is highly factual, whereas a rating of seven means that it is highly impression-based. Both our judges are females, with considerable experience in purchasing women's clothing on the Internet. We have asked them to evaluate the nature of product information provided by each of the three technologies – zoom, alternative photos, and color swatch – for the same set of over 500 products and to assign a rating for each technology corresponding to each product. They have been provided with the definitions of factual and impression-based information as described in Holbrook (1978) in advance, and have worked independently, on one product at a time, at their own pace.

We find that the two judges' ratings have high inter-rater agreement scores as measured by the kappa statistic (Gwet 2010). The kappa statistic is 0.79 for zoom, 0.66 for alternative photos, and 0.73 for color swatch. Thus, the two judges' ratings have "substantial agreement," as characterized by Landis and Koch (1977), only one level below "almost perfect agreement", which is the highest level of inter-rater agreement.<sup>3</sup> In light of these high kappa values, we have asked the first judge to complete the ratings for all the remaining products (approximately 1,300 more products).

Since we have asked the judges to use a seven-point scale ranging from "highly factual" to "highly impression-based," a mean value of significantly lower than four, which is the midpoint, implies that the focal technology provides predominantly factual information to consumers. In contrast, a mean of significantly higher than four implies that the focal technology provides predominantly impression-based information. Based on the first judge's ratings over all the products, the zoom technology has a mean of 1.19 and a standard error of 0.01, the alternative photo technology has a mean of 5.40 and a standard error of 0.02, and the color swatch technology has a mean of 4.28 and a standard error of 0.03. The results from t tests show that all these mean values are significantly different from four.

Our explanations of the rating results are as follows. With the use of zoom, consumers are able to see some finer details of the focal product. In our context of clothing products, such finer details include the product's fabric, pattern, print, stitches, and small decorative features (buttons, ties, etc.). These details convey mostly factual information about the focal product to consumers, as evidenced by the mean rating of 1.19, which is significantly lower than four.

The alternative photo technology has two important functions (Daugherty et al. 2005): it enables consumers to see the focal product's rotation (i.e., different sides) as well as contextualization (i.e., the placement of the product in an appropriate context to simulate how the product can be used). Rotation contains mostly factual information about how the focal product looks from the front, back, and sides, whereas contextualization contains mostly impression-based information. In our context, a consumer sees additional pictures of a beautiful model wearing the focal product, typically in a scenic environment, from different angles. All of these pictures, taken by professional photographers, are designed to convey ideas or impressions regarding how a consumer may look herself while wearing the product. Hence, while the consumer may gain some factual information by observing the model from different angles, the use of alternative photos is likely to draw her attention toward impression-based (or evaluative) information.

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<sup>3</sup> Landis and Koch (1977) characterize Kappa values 0-0.2 as indicating slight agreement, values 0.21-0.4 as fair agreement, 0.41-0.6 as moderate agreement, 0.61-0.8 as substantial agreement, and 0.81-1 as almost perfect agreement.

Apparently, in our research setting, the information conveyed via contextualization is more impactful than what is conveyed via rotation, as evidenced by the mean rating of 5.40, which is significantly higher than four.

In our context, consumers see all the available colors for a product, shown in small color patches, when visiting the main product page. By using the color swatch technology, she can see the product in each of these colors separately on a larger frame and may obtain a more vivid view of the color than just by looking at the small color patch. A more vivid viewing of the color helps the consumer gain factual information. On the other hand, the color swatch technology enables her to visualize how the focal product in a certain color would look on a beautiful model in a scenic environment, conveying impression-based information to her. Thus, the color swatch technology provides both factual and impression-based information, with perhaps a slightly more weight on the impression-based information, as evidenced by the mean rating of 4.28, which is quite close to four but still significantly different from it in a statistical sense (evidently because of the low standard error).

Based on the above discussions, and in light of the propositions described earlier, we can hypothesize how consumers' use of different product-oriented technologies affects their tendency to return products. The use of the zoom technology is expected to have a negative effect on the likelihood of product returns via the provision of mostly factual information. The use of the alternative photo technology is expected to have a positive effect on the likelihood of product returns via the provision of primarily impression-based information. Finally, the use of the color swatch technology, too, is expected to have a positive effect on the likelihood of product returns, although this effect is likely to be small compared to the effect of the alternative photo technology. In summary, we arrive at the following three hypotheses.

**Hypothesis 1:** *The use of the zoom technology has a negative effect on product returns.*

**Hypothesis 2:** *The use of the alternative photo technology has a positive effect on product returns.*

**Hypothesis 3:** *The use of the color swatch technology has a positive effect on product returns.*

### **3. Research Design**

#### *3.1. Data Description*

The data for this research comes from a large women's clothing retailer. The company's website provides consumers with navigational features such as browsing, a search function, and a recommendation system, which help them access a broad set of products. On each product page, there are

three product-oriented technologies available, namely, zoom, alternative photos, and color swatch. Once a visitor is on the product page, she can use these technologies to gain additional information – factual or impression-based – on the focal product.

Our dataset contains information on all orders placed through the company’s Internet channel (and also its catalog channel) from May 2003 to April 2006. For each item purchased from the company, we have information regarding the price paid, date of transaction, consumer’s unique identification, whether or not the item was returned, ordering channel (i.e., Internet or catalog), and purchase identification. Overall, we have the data for 7 million purchases that were made by approximately 1 million unique consumers. We also have server logs recorded at the company’s website from March 2006 to April 2006, capturing each page request made by each visitor during this time. These server logs follow the standard World Wide Web Consortium extended log-file format. We have approximately 52 million lines of logs for these two months, amounting to about 850,000 page requests per day.

This company promotes its products by sending catalogs and emails. For each product featured in the catalog, it provides a picture of a model wearing the product, price, available colors, and sizes. We have information regarding the catalogs received by each consumer between January 2005 and April 2006. While each consumer with a valid email address receives all emails, all consumers do not receive every catalog.

### *3.2. Sample*

Matching each consumer’s technology usage with the returns made by the same consumer requires the identification of the website sessions carried out by each consumer. Fortunately, when a consumer makes a purchase online, the same web order identification is recorded in both the server log and the purchase database, enabling us to identify all the purchase sessions carried out by the consumer. As the objective of this paper is to study the impact of technology usage on returns, we only consider those consumers who made at least one Internet purchase and, consequently, had an opportunity to return. Since the catalogs may provide some product-oriented information and influence the expectation, we select those consumers who received all the catalogs sent out between February 1, 2006 and April 30, 2006 and made at least one Internet purchase in April 2006.<sup>4</sup> Following the existing studies on product returns (e.g., Anderson et al. 2009, Petersen and Kumar 2009), we consider only purchased products in

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<sup>4</sup> Our analysis of the data shows that the impact of a catalog typically lasts for about 30 days, which is consistent with the retailer’s past experience. Therefore, in order to be conservative, we use a time frame from February 1, 2006 (i.e., 59 days prior to April 1, 2006) to April 30, 2006.

our main analysis.<sup>5</sup> We study the relationship between these consumers' technology usage and the returns they made on the products purchased in April 2006. In our final sample, we have 34,490 (non-unique) products purchased by 10,205 (unique) consumers.<sup>6</sup> Of these purchased products, 9,189 were returned by 3,691 consumers.

We measure the use of each of the technologies by a consumer for a particular product by counting the number of times the focal technology was used for the product. It is possible that consumers used technologies in earlier sessions (i.e., non-purchase sessions) for the product; therefore, it is critical to include the use of technologies from non-purchase sessions as well. Since the company's server log records a unique cookie number for each consumer, we have used the cookie number in each consumer's purchase sessions to identify all the non-purchase sessions of the same consumer. In addition to all the purchase sessions in April 2006, we include technology usage from the sessions 30 days prior to the purchase sessions, a grace period consistent with previous studies (e.g., Sismeiro and Bucklin 2004).

### 3.3. Key Variables

Our primary dependent variable *Return* is an indicator variable, which takes a value 1 if the product is returned. We define the technology usage variables as follows: *Zoom Usage* refers to the number of times the zoom technology was used by a consumer for the focal product; *Alternative Photo Usage* refers to the number of times the alternative photo technology was used similarly; and, finally, *Color Swatch Usage* refers to the number of times the color swatch technology was used similarly.

In addition to the three independent technology usage variables, we use three control variables for our analyses. First, *%Discount* refers to the discount received by a consumer in purchasing the product<sup>7</sup> – a high discount may lower the likelihood of return. Second, *List Price* refers to the list price of the product – it is likely that the return propensity would be higher for a more expensive product compared to a cheap product, given the same level of dissatisfaction. Finally, *Times Viewed* refers to the number of times a consumer visited the product page, which may represent a consumer's hesitation in buying the product. Table 1 presents the descriptive statistics of all the variables.

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<sup>5</sup> In section 4.3, we also examine the products the consumers in our sample considered but did not purchase to account for the effects of product-oriented technologies on sales while studying the effects of these technologies on returns.

<sup>6</sup> If the same product is purchased by two consumers, it is counted as 2. On the other hand, if a consumer purchases multiple units of the same product, it is counted as 1. This is because the impact of technology usage is the same irrespective of whether she purchases/returns one or multiple units of the product. In other words, the counting is done at the consumer-product level, not at the product-unit level. We have a few cases (878) where multiple units of a product were purchased and only a subset of them was returned. Our results are robust to including or excluding these cases.

<sup>7</sup> The discount is calculated as  $(\text{List Price} - \text{Purchase Price}) / \text{List Price}$ .

**Table 1:** Descriptive Statistics of Variables

Variable	Mean	Std. Dev.	25 <sup>th</sup> Percentile	50 <sup>th</sup> Percentile	75 <sup>th</sup> Percentile	Max
Returns	0.266	0.442	0	0	1	1
Zoom Usage	0.067	0.663	0	0	0	54
Alternative Photo Usage	1.016	2.166	0	0	1	53
Color Swatch Usage	0.240	0.848	0	0	0	18
%Discount	0.112	0.172	0	0.007	0.209	0.833
List Price	35.217	14.108	29.0	32.0	39.470	179.0
Times Viewed	3.471	4.760	1	2	4	128

## 4. Empirical Analysis

### 4.1. Main Model

In our dataset, for each consumer  $i$ , we have a binary outcome  $Return_{ij}$  for each product  $j$ . We consider the following model in latent variable form (Wooldridge 2002):

$$Return_{ij}^* = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \beta_3 X_{3ij} + \beta_4 C_{1ij} + \beta_5 C_{2ij} + \beta_6 C_{3ij} + \mu_i + \varepsilon_{ij} \quad (1)$$

$$Return_{ij} = 1 [Return_{ij}^* > 0]$$

where  $X_1$ ,  $X_2$ , and  $X_3$  denote *Zoom Usage*, *Alternative Photo Usage*, and *Color Swatch Usage*, respectively;  $C_1$ ,  $C_2$ , and  $C_3$  are the control variables – *%Discount*, *List Price*, and *Times Viewed*, respectively;  $\mu_i$  represents the unobserved consumer heterogeneity; and finally,  $\varepsilon_{ij}$  is the random error.

### 4.2. Results

Equation (1) is a discrete choice model. Allowing for random unobserved heterogeneity  $\mu_i$  in our panel dataset, we estimate the equation using a random effects logit model. Table 2 presents the results of this estimation.<sup>8</sup>

As expected, we find that the effect of technology usage on returns is not homogeneous; rather, it is mixed. *Zoom Usage* has a negative coefficient, significant at 10%, which suggests that a higher usage of the zoom technology decreases the likelihood of returns. *Alternative Photo Usage* has a positive coefficient, significant at 1%, which strongly suggests that a higher usage of the alternative photo technology increases the likelihood of returns. *Color Swatch Usage*, however, has an insignificant impact on returns. Thus, we find support for H1 and H2, while H3 is not supported. It appears from these results

<sup>8</sup> We have tested for multicollinearity and found that it is not a concern in our analyses. We have also used binary indicators for the technology usage variables (i.e., the technology in question was used or not used) instead of the usage counts, and obtained qualitatively similar results.

that, among the different product-oriented technologies, the alternative photo technology has the most salient influence on product returns. In terms of the economic significance, we find that the odds ratio for *Zoom Usage* is 0.93, implying that one unit increase in *Zoom Usage* leads to a 7% decrease in the odds for returning a product (Jaccard 2001). One unit increase in *Alternative Photo Usage*, on the other hand, increases the odds for returning a product by 5% (its odds ratio is 1.05).

**Table 2:** Effects of Technology Usage on Product Return Propensity

	<b>Logit (1)</b>
Zoom Usage	-0.068* (0.037)
Alternative Photo Usage	0.048*** (0.014)
Color Swatch Usage	-0.015 (0.024)
%Discount	-0.431*** (0.132)
List Price	0.011*** (0.001)
Times Viewed	0.028*** (0.006)
Intercept	-2.873*** (0.077)
Log Likelihood	-15,970.12
Number of Consumers	10,205
Observations	34,490

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

Obviously, the question arises why H3 is not supported. As we mentioned before, for the website of this company (as well as the websites of Internet retailers in general), all possible colors for the product are already shown even before a consumer clicks on a specific color. So, the additional information she gains by clicking and seeing the product in the chosen color is perhaps quite limited. Moreover, as discussed earlier, this additional information may be neither predominantly factual nor predominantly impression based. Therefore, even though the use of this technology, like the use of the other two technologies, may influence returns, the net effect of this technology is not likely to be significant. Hence, it is not surprising that the coefficient of *Color Swatch Usage* has turned out to be insignificant.

#### 4.3. Considering the Impact of Technology Usage on Sales

Our analysis so far has considered purchased products only, consistent with the existing literature on product returns (Anderson et al. 2009, Petersen and Kumar 2009). There may, however, be concerns

that this approach does not account for the impact of the use of the product-oriented technologies on non-purchased products, creating a sample selection bias. Fortunately, we also have the data on non-purchased products considered by the consumers in our sample and, therefore, are able to supplement our main analysis to check if our results hold even when we consider the impact of technology usage on sales. Specifically, we have panel data (at the product level for each consumer), showing each consumer's purchase and return choices (both binary choices – purchased or not, and returned or not) for each product (in total, 183,217 observations).

**Table 3: Two-Stage Model**

	<b>First Stage (1)</b>	<b>Second Stage (2)</b>
Zoom Usage	-0.013 (0.013)	-0.032** (0.015)
Alternative Photo Usage	0.014*** (0.003)	0.015** (0.006)
Color Swatch Usage	0.063*** (0.006)	-0.015 (0.010)
%Discount		-0.247*** (0.063)
List Price	-0.003*** (0.000)	0.005*** (0.001)
Times Viewed	0.633*** (0.011)	0.011*** (0.003)
Promoted	0.419*** (0.013)	
Intercept	-1.430*** (0.017)	-0.604*** (0.058)
Log Likelihood		-102,280.02
Observations	183,217	34,490

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

To the best of our knowledge, a discrete choice model with sample selection for panel data does not exist. We have, however, been able to indirectly account for the panel data structure by clustering the errors for each consumer, and to utilize a two-stage probit model with sample selection that considers discrete choices in both stages (the heckprob command in Stata) (Greene 2011). The first stage measures the effect of technology usage on purchases/sales and the second stage measures its effect on returns. An added advantage of this approach is that we can now study the effect of technology usage on net sales (i.e., sales minus returns).

In the first stage, we use all the variables of the original model or equation (1) (which is used here in the second stage), plus an additional identification variable, *Promoted*, defined as whether or not the focal product is featured in a catalog (see section 5.4 for more details on this variable). We cannot, however, control for *%Discount* in the first stage because the discount cannot be calculated for non-purchased products as there is no purchase price for such products (see footnote 7). The results are presented in Table 3.<sup>9</sup> Comparing the results of the second stage with those of Table 2, we note that they are qualitatively similar. It is not surprising that they are, however, not very close quantitatively; this is because the results of Table 2 are based on a logit model, whereas those of Table 3 come from a probit model (see also the discussion regarding the second column of Table 4 in section 5.1).

We also calculate the marginal effects of these technologies on returns, taking into consideration their effects on sales (using the `mfx` command in Stata after the `heckprob` command). We find that the marginal effect of *Zoom Usage* is -0.012 (p-value: 0.03), i.e., increasing one unit of *Zoom Usage* leads to a 0.012 reduction in the probability of the net outcome (impact on returns – impact on sales) or, equivalently, a 0.012 increase in the probability of net sales. The marginal effect of *Alternative Photo Usage* is 0.005 (p-value: 0.02), i.e., one unit increase in *Alternative Photo Usage* boosts the probability of the net outcome, or decreases the probability of net sales, by 0.005. This suggests that *Alternative Photo Usage* is detrimental to the retailer even when we consider its impact on sales and returns together.

## 5. Robustness Checks and Additional Analyses

### 5.1. Alternative Estimations

As noted before, we use a random effects logit model for our main analysis. Thus, we do not assume that the individual unobserved heterogeneity  $\mu_i$  remains constant across different products. An added advantage is that we are able to retain all observations (even the ones without any variability) for our analysis. However, the implicit assumption here is that  $\mu_i$  is not correlated with the independent variables. We now check the robustness of our main results by estimating a fixed effects logit model. Accordingly, we estimate equation (1) by considering the unobserved heterogeneity factors for our panel dataset as fixed effects. The strength of this approach is that it allows arbitrary correlations between  $\mu_i$  and the independent variables (Baltagi 2008; Wooldridge 2002). On the other hand,  $\mu_i$  is now assumed to be independent of the products. Moreover, we can retain only those consumers who had some variation in their return behavior; in other words, we need to discard all consumers who always returned or never returned. Consequently, the sample size is considerably smaller in this case. The results of the fixed

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<sup>9</sup> Because of the presence of high multicollinearity in the first stage when we use a count for *Times Viewed*, we use a dummy indicator for it in this stage, which captures whether the value is above or below the median.

effects logit model are presented in column (1) of Table 4. As is often the case with fixed effects models, the significance levels of coefficients are now lower. Reassuringly, the results are still qualitatively similar to those of Table 2.

**Table 4:** Results with Alternative Models

	<b>FE Logit (1)</b>	<b>Probit (2)</b>	<b>Random Coefficients Logit (3)</b>
Zoom Usage	-0.048 (0.042)	-0.039* (0.022)	-0.077* (0.040)
Alternative Photo Usage	0.029* (0.017)	0.029*** (0.008)	0.038* (0.020)
Color Swatch Usage	-0.013 (0.026)	-0.008 (0.014)	-0.051 (0.035)
%Discount	0.011 (0.147)	-0.265*** (0.076)	-0.425*** (0.136)
List Price	0.009*** (0.002)	0.007*** (0.001)	0.011*** (0.002)
Times Viewed	0.025*** (0.007)	0.016*** (0.004)	0.030*** (0.007)
Intercept		-1.639*** (0.044)	-2.839*** (0.079)
Log Likelihood	-5,093.22	-15,943.24	-15966.70
Number of Consumers	2322	10,205	10,205
Observations	12,323	34,490	34,490

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

There may be concerns that  $\mu_i$  may not only vary across the products, which is considered in the random effects logit model, but it may also be correlated across different products for the same consumer. In such cases, the appropriate estimation technique for a panel dataset is the random effects probit model (Train 2009). To check the consistency of the logit results, we estimate equation (1) using a panel data probit model as well. The results of this model, which are presented in column (2) of Table 4, are qualitatively similar to those in Table 2. Not surprisingly, the estimates of this model are quite similar to those of column (2) in Table 3. They are not, however, identical because the two-stage sample selection model, as mentioned before, does not directly account for the panel structure of the data.

It is possible that different consumers not only have heterogeneous intercepts ( $\mu_i$ ), which is considered in the random effects logit and probit models, but also have different slopes (i.e., random coefficients). In such situations, one can use random coefficients logit (Rabe-Hesketh and Skrondal

2008)<sup>10</sup>, which we employ for further checking the robustness of our results. These results, which are presented in column (3) of Table 4, are also qualitatively similar to those of Table 2.

### 5.2. Addressing Technology Self-selection and Potential Endogeneity

There may be concerns about consumers' self-selection with technology usage and the ensuing effects on returns. One way of addressing these concerns regarding technology self-selection is to analyze the sub-sample that excludes the consumers who always used technology or never used technology. Effectively, this would discard those who self-selected to be avid technology users as well as those who always avoided technology. We re-estimate our main model with this sub-sample and present the results in Table 5. Once again, we find qualitatively similar results.

**Table 5:** Results without Avid Technology Users and Technology Avoiders

	<b>Logit (1)</b>
Zoom Usage	-0.056 (0.037)
Alternative Photo Usage	0.044*** (0.015)
Color Swatch Usage	-0.013 (0.024)
%Discount	-0.327** (0.137)
List Price	0.011*** (0.002)
Times Viewed	0.028*** (0.006)
Intercept	-2.751*** (0.082)
Log Likelihood	-13,273.74
Number of Consumers	7,405
Observations	28,440

Standard errors are in parentheses; \*\*\* p<0.01;\*\* p<0.05;\* p<0.10

There may also be concerns that a consumer's usage of product-oriented technologies for a product and the propensity to return the product are both influenced by certain factors. We have already controlled for *Times Viewed*, which captures a consumer's uncertainty regarding the product. In addition, we allow for random unobserved heterogeneity in our random effects models. Still, we test for potential endogeneity using the widely used propensity score matching method suggested by Rosenbaum and

<sup>10</sup> We thank David Brownstone for guidance with this method.

Rubin (1983). Since the correlations among the three product-oriented technology usages are negligible, we consider each of these variables separately. Accordingly, for each product-oriented technology, we obtain a sample of the control group (e.g., consumers who did not use alternative photos) that matches the treatment group (i.e., consumers who used alternative photos) on the observable dimensions. Thus, we are able to drastically reduce the difference between the control group and the treatment group in order to control for any selection bias.

**Table 6:** Results after Propensity Score Matching

	(1)	(2)	(3)
Zoom Usage	-0.060** (0.025)	-0.058** (0.022)	-0.036 (0.038)
Alternative Photo Usage	0.026* (0.016)	0.025*** (0.007)	0.034* (0.019)
Color Swatch Usage	0.012 (0.035)	-0.011 (0.016)	0.009 (0.017)
%Discount	-0.532 (0.333)	-0.524*** (0.078)	-0.464*** (0.153)
List Price	0.005* (0.003)	0.006*** (0.001)	0.013*** (0.002)
Times Viewed	0.018** (0.008)	0.022*** (0.003)	0.019** (0.008)
Intercept	-1.178*** (0.144)	-1.242*** (0.037)	-1.564*** (0.064)
Log Likelihood	-1086.42	-17510.44	-4596.56
Observations	1,830	29,942	8,326

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

The first step is to create an indicator variable identifying whether an observation belongs to the treatment group (i.e., observation with positive technology usage), and estimate a logit model with this dummy variable as the dependent variable and the observable variables as independent variables (in addition to the independent variables used in Equation (1), we also include the consumer’s historical purchases – recency and frequency of past web purchases along the lines of prior research (e.g., Anderson and Simester (2004)).<sup>11</sup> Next, we perform a nearest-neighbor matching algorithm (without replacement) based on the propensity scores calculated in the previous step to identify a matched control group.<sup>12</sup> Finally, we estimate a logit model of Equation (1) on a “matched sample” that includes the matched control group and the original treatment group. Columns (1), (2), and (3) of Table 5 present the results

<sup>11</sup> Here, recency is defined as the number of days from the date of the last purchase to April 1, 2006, and frequency as the number of orders prior to April 1, 2006.

<sup>12</sup> We have used the STATA PSMATCH2 module by E. Leuven and B. Sianesi. Our results are robust to using other matching algorithms and using a Probit model instead of a Logit model.

for the three technologies – zoom, alternative photos, and color swatch – respectively. Reassuringly, these results are quite similar to those in Table 2.

### 5.3. Controlling for product categories

There may be concerns that the inherent return tendency is different across product categories and, thereby, confounds the results. The products of the retailer we study can be categorized primarily into two groups – swimwear and fashion clothing. We repeat the main analysis with an additional dummy variable that indicates whether a product belongs to fashion clothing. The results are reported in Table 7 and demonstrate that our findings are robust to controlling for product categories. Note that the dummy is insignificant, which suggests that there is no additional return tendency for either category of products.

**Table 7:** Results after Controlling for Product Categories

	<b>Logit (1)</b>
Zoom Usage	-0.068* (0.037)
Alternative Photo Usage	0.048*** (0.014)
Color Swatch Usage	-0.015 (0.024)
%Discount	-0.429*** (0.133)
List Price	0.011*** (0.001)
Times Viewed	0.028*** (0.007)
Clothing Dummy	-0.009 (0.052)
Intercept	-2.868*** (0.082)
Log Likelihood	-15,970.10
Number of Consumers	10,205
Observations	34,490

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

It is also possible that the role of different product-oriented technologies may vary across these two product categories. To test this possibility, we include the interaction effects between technology usage and the product categories in our analysis. The results, presented in Table 8, show a stronger impact of product-oriented technology usage in the fashion clothing category, whereas the effect is milder

for the swimwear category.<sup>13</sup> In particular, the impact of zoom is insignificant for swimwear, whereas it is negative and significant for fashion clothing. Similarly, the impact of alternative photo is larger on fashion clothing compared to swimwear. This contrast is in line with the fact that there is relatively less room for gaining information to influence pre-purchase expectations in swimwear compared to fashion clothing. It is because the items in the swimwear category are quite standardized in terms of style, while those in fashion clothing may vary greatly from one to another. Consequently for the latter, consumers have a stronger need to form pre-purchase expectations regarding how they would look wearing these products. Moreover, they now have more room to glean information – either factual or impression based depending on the technology used – to form these expectations.

**Table 8:** Results for Interaction Effects between Technology Usage and Product Categories

	<b>Logit (1)</b>
Zoom Usage	-0.018 (0.045)
Alternative Photo Usage	0.033** (0.016)
Color Swatch Usage	0.023 (0.071)
Clothing Dummy* Zoom Usage	-0.120* (0.070)
Clothing Dummy* Alternative Photo Usage	0.076*** (0.027)
Clothing Dummy* Color Swatch Usage	-0.050 (0.075)
%Discount	-0.448*** (0.133)
List Price	0.011*** (0.001)
Times Viewed	0.032*** (0.007)
Intercept	-2.884*** (0.077)
Log Likelihood	-15,965.06
Number of Consumers	10,205
Observations	34,490

Standard errors are in parentheses; \*\*\* p<0.01;\*\* p<0.05;\* p<0.10

<sup>13</sup> We also separate the sample into two parts based on these two product categories, and repeat the main analysis for each part. The results remain qualitatively similar.

#### 5.4. Controlling for the effects of promotion

When a product is featured in a catalog, it may capture some attention of potential consumers. As such, they are likely to have some information about the featured products before coming to the website and using product-oriented technologies. More product information can potentially lower the possibility of product returns. In order to alleviate any concerns related to the effects of product promotions through catalogs, we include a control variable indicating whether or not a product was featured in the catalogs received by the consumers (between February 1, 2006 and April 30, 2006 – see footnote 4). Table 9 presents the estimates of Equation (1) using a random effects logit model with the additional control variable *Promoted*. Our main findings remain qualitatively unchanged even after controlling for such promotional effects. We also note that, as expected, the coefficient of *Promoted* is negative and significant, indicating that the products which are featured in the catalog are less likely to be returned compared to other products.

**Table 9:** Results after Controlling for the Effects of Promotion

	<b>Logit (1)</b>
Zoom Usage	-0.069* (0.037)
Alternative Photo Usage	0.048*** (0.015)
Color Swatch Usage	-0.018 (0.024)
%Discount	-0.651*** (0.153)
List Price	0.012*** (0.001)
Times Viewed	0.030*** (0.006)
Promoted	-0.204*** (0.070)
Intercept	-2.685*** (0.100)
Log Likelihood	-15965.95
Number of Consumers	10,205
Observations	34,490

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

#### 5.5. Moving to the consumer level

So far, we have analyzed the impact of technology usage at the consumer-product level. One might also be interested in the aggregate effect of technology usage by a consumer on her return

propensity. Hence, in this section, we aggregate the independent variables at the consumer level (we take the average for %Discount; moreover, List Price is excluded since the analysis is no longer at the consumer-product level and determining an aggregate list price is not meaningful). The dependent variable is Return Rate, i.e., the fraction of the products that were returned. We use a generalized linear model (GLM) to express it (Papke and Wooldridge 1996):

$$E(r_i | X_i) = \frac{e^{X_i\beta}}{1 + e^{X_i\beta}} \quad (2)$$

where  $r_i(0 \leq r_i \leq 1)$  is the fraction of the products returned in the overall sales to consumer  $i$  in April 2006; and  $X_i$  is a vector of explanatory variables.

The results are reported in Table 10. Note that the number of observations in this table is significantly lower than before because of the aggregation; in fact, it is the same as the number of consumers. Consistent with the finer level analysis, we find that *Total Alternative Photo Usage* has a positive and significant effect on returns. The impact of zoom is still negative, but not significant anymore. As before, %Discount plays a significant role in reducing returns. Instead of *Total Times Viewed*, one could use the total quantity purchased by a consumer. Since these two variables are highly correlated, they cannot, however, be used in the model together. We have tried the model with total quantity and found the results to be quite similar.

**Table 10:** Results on Return Rates at the Consumer Level

	GLM (1)
Total Zoom Usage	-0.017 (0.012)
Total Alternative Photo Usage	0.014*** (0.004)
Total Color Swatch Usage	0.001 (0.008)
Mean %Discount	-1.091*** (0.153)
Total Times Viewed	0.004*** (0.001)
Intercept	-1.166*** (0.028)
Log Likelihood	-4991.09
Observations	10,205

Standard errors are in parentheses; \*\*\* p<0.01; \*\* p<0.05; \* p<0.10

## 6. Summary and Conclusion

This paper analyzes the relationship between product-oriented technologies and product returns using various econometric models and an information-rich dataset. Our results show that the effect of technology is not uniform; rather, it varies depending on the specific technology used. In particular, the use of the zoom technology, which provides mostly factual information, reduces the propensity to return. On the other hand, the use of the alternative photo technology, which provides mainly impression-based information, leads to more returns. Finally, the color swatch technology has an insignificant effect on returns. These results survive an array of robustness checks. We provide plausible explanations for all the findings based on the extant literature.

This study has both academic and managerial implications. On the academic front, we enrich the understanding of consumers' return behavior by unraveling the effects of product-oriented technologies on returns. While there have been a few recent studies investigating the impact of technology usage on sales, to the best of our knowledge, no one has yet studied the relationship between technology usage and returns. Moreover, this is the first empirical study, using real transaction data – matched with technology usage data gleaned from server logs – to shed light on the linkage among pre-purchase expectation, post-purchase satisfaction, and return. This is also the first study that examines how different product-oriented technologies provide different types of information and, in turn, how these different types influence product returns differently. In addition, our analysis is at a finer level than before – at the product level for each consumer, rather than at the consumer level (see, for example, Petersen and Kumar 2009). This is consistent with the new emphasis on the use of micro-level data in IS research (Wu et al. 2008, Overby and Jap 2009).

From a managerial perspective, the findings in this paper are important because most Internet retailers now provide product-oriented technologies on their websites. Our findings are, therefore, likely to be useful for retailers at large, although this specific study uses data from a clothing retailer. The insights gained from this paper should help firms decide whether and how they should invest in developing and maintaining these expensive technologies in order to reduce returns. For example, we find that one unit increase in alternative photo usage can increase the odds for return by 5%. Perhaps more importantly, when we consider the impact of this technology on both sales and returns, we observe an increase in the net outcome (impact on returns – impact on sales) or a decrease in net sales. Thus, although the use of this technology may lead to higher sales, it may increase returns so much that the retailer suffers a net loss. It would, therefore, be beneficial for retailers to present pictures that could help consumers form realistic pre-purchase expectations of a product. In fact, some major companies have already started paying attention to this phenomenon, Amazon being a trend setter in this respect. These

companies allow consumers to upload and share images that show the product in use, illustrate how the product performs, or provide a sense of the size of the product. Amazon, for example, states: “Customer images are like visual reviews. By sharing your images, you can help other customers understand how products look and perform” (Newcomb 2004). More and more companies – such as Wal-Mart, Urban Outfitters, Zales, and even Petco – have joined this trend recently (Bryan 2011).

We note that the effect of using the alternative photo technology, in particular, may vary from one product category to another. In a product category like laptops, the rotation effect may dominate the contextualization effect because each side of a laptop may provide important facts (e.g., how many and what type of slots there are to hook up other devices or cables). Hence, the information consumers obtain through alternative photos in such a scenario is likely to be primarily factual. The situation may, however, be quite different for a category like furniture. Online furniture retailers often show pictures of nicely appointed furniture in an attractive ambiance. While a consumer may learn a few additional facts by observing the product from different sides, the ambiance may play a major role here. Consequently, the contextualization effect may dominate the rotation effect, making the information primarily impression based, as in the case of women’s clothing examined in this paper. Thus, it is especially important to consider the dominance of the type of information while analyzing the impact of the alternative photo technology on product returns. In fact, as stated before, consideration of the type of information while examining product returns is one of the major contributions of this paper. Moreover, the comprehensive approach adopted here using various econometric techniques is generalizable to any product category.

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