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Information Search and Product Returns Across Mobile and Traditional Online Channels

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Abstract

Product returns will soon cost firms a trillion dollars annually and e-commerce is detrimentally affected the most, compared to offline channels. To facilitate firm operations, strategic insights are needed to better understand what factors increase the return propensity of customers and when the short-term costs of returns can be offset by future customer purchases. To address these gaps, we execute two studies using transaction data across two large apparel e-tailers. Study 1 demonstrates that consumers engage in fundamentally different information searches on mobile versus traditional online channels, and this difference in search spills over to impact return rates. The return rates are lower in the mobile channel and utilization of the mobile channel can alter the effect of discount promotions. Study 2 suggests that future spending by consumers following a return is contingent on category characteristics. In categories that facilitate learning from customers' previous return experience, product returns positively increase future spending, but the opposite is true in categories where limited learning takes place.

Keywords: E-commerce
E-tailer
Product Returns
Channel Utilization
Customer Learning

Introduction

The retail industry has changed dramatically over the last two decades, initially due to the arrival of traditional online shopping via a computer interface and, more recently, with the proliferation of mobile channels and social media platforms (e.g., Verhoef, Kannan, and Inman 2015). Statistics show that US e-commerce sales as percentage of total retail sales was expected to be 12.4% in 2020 and 13.7% in 2021 (doubling in 5 years), but those figures were forecasted prior to the coronavirus pandemic.[1] The coronavirus pandemic is adding pressures to retailing dynamics worldwide, and the year-end 2020 and 2021 ratio of online-to-offline shopping will likely be much higher than the predicted significant increases in online retailing.[2] Due to the coronavirus pandemic, almost every product category has grown by at least 10% in online sales and most much more (e.g., grocery & gourmet food, appliances, health & household, toys & games, and garden products).[3] Are retailers strategically ready for the product returns that will result from consumers affinity for online shopping and, more importantly, are retailers ready for a post-coronavirus world where online shopping potentially makes a leaping jump in market share vis-à-vis brick-and-mortar offline shopping?

Even before the pandemic, one of the most significant concerns in online retailing was product returns, as a recent consumer survey showed that at least 30% of all products ordered online are returned as compared to 9% bought in brick-and-mortar stores (Reagan 2019). For example, Tobin Moore, the CEO of Optoro said: "in the next several years, as e-commerce grows globally, the amount of returns is going to be over a trillion dollars a year."[4] Additionally,

1 https://www.statista.com/statistics/379112/e-commerce-share-of-retail-sales-in-us/.
2 As a note for clarity, the official scientific name of the coronavirus that caused the global pandemic is SARS-CoV-2 and the disease itself is called COVID-19.
3 https://sellics.com/blog-coronavirus-covid-amazon-online-shopping/
4 https://www.cnbc.com/2019/01/10/growing-online-sales-means-more-returns-and-trash-for-landfills.html

UPS (United Parcel Service) estimates that one million returns were made every day during December 2018 leading up to Christmas. The situation has become so difficult logistically that even the e-commerce giant Amazon has banned some customers from shopping on its platform because they have returned too many items[5]. The famous return any time after purchase policy of L.L. Bean was terminated in February 2018 due to its huge cost brought to the company's bottom line.[6] Ultimately, product returns represent a significant business expense to vendors and the emergence of multiple online shopping channels, which alter the consumer shopping process, has thrown even more uncertainty into how these return problems might evolve (Reagan 2019).

Historically, brick-and-mortar stores processed returns with limited reverse logistics costs and lower return frequency (5-10% return rate versus 15-40% for e-tailers, Reagan 2019). The main reason for increased return rates for e-tailers stems from the fact that customers cannot touch and feel a product before purchasing it (higher rate of misjudgement) (Kau, Tangm, and Ghose 2003), which becomes more problematic as online channels display a seemingly infinite number of substitute products (low search costs) (Hung 2012; Lynch and Ariely 2000; Reichheld and Schefter 2000). In an effort to validate these assertions, we conducted a brief survey among customers who recently made an online purchase and then returned it. Of the 156 survey participants, 29% of the participants state they returned a product, because it was not as good as described online and 51% said when they tried the product, it was not as good as they had expected. Given these realities, coupled with the ubiquity of both traditional online shopping and mobile internet shopping in e-tailing and more importantly, the potential differences between these shopping channels, there is a need for a more robust and practical perspective and

5 https://www.wsj.com/articles/banned-from-amazon-the-shoppers-who-make-too-many-returns-1526981401
6 https://www.businessinsider.com/how-to-return-ll-bean-items-after-policy-change-2018-2

understanding of how customers' return behaviors change as they transition to these shopping channels.

However, the extant literature offers only limited solutions to mitigate the problem of product returns. Bell, Gallino, and Moreno (2015), for example, suggest that having show-and-tell opportunities (i.e., offline showrooms) that complement online channels can lead to lower return rates by helping to solve the primary issue of lack of fit. However, the substantial costs of showroom operations and the limited coverage compromises the effectiveness of this strategy. Anderson, Hansen, and Simester (2009) and Bower and Maxham (2012) state that if product returns are at the customers' expense, a customer is less likely to return products. However, implementing such a negatively-oriented strategy has been shown to adversely affect customers' future purchase intentions (Bower and Maxham 2012). Thus, while strategies like these might help the bottom line in the short run, they will likely damage business in the long run.

Also, extant research only offers some remedies to catalog retailers (i.e., Anderson et al. 2009), and retailers who still operate both brick-and-mortar stores and online stores (i.e., Ofek, Katona, and Sarvary 2011, see Table 1 for more references). However, the realities are more retailers have become pure e-tailers who only operate online to control their operational costs and stay in business. As indicated, they are more likely to be victims of high product return rates. Thus, levers for those e-tailers to utilize, in particular, to reduce their return rates are still needed.

Furthermore, although intuitive thinking suggests that returns hurt firm performance, there could be a silver lining in returns. Specifically, Petersen and Kumar (2009; 2010; 2015) articulate that a reasonable number of product returns may maximize firm profits over the long run. The premise is that return behaviors can lower customers' perceived risk of current and future purchases and a satisfying return experience can lead to future business. Altogether, prior research demonstrates that returns offer the potential to both help and harm the firm, but there is not much research that informs the contexts that swing the returns process from a cost with no benefits to a relationship marketing tool that can be used to generate future business.

To bridge all above gaps in the literature, our research takes a deeper look at both behavioral *antecedents* and *consequences* of returns, particularly for e-tailers. Specifically, we leverage transaction data from two of the largest apparel firms (e-tailers) selling on Alibaba to test the role that marketing channel utilization (mobile channels and traditional online channels[7]) plays in driving returns, and how customer learning alters the consequences of returns. Drawing from information search and assimilation research, this research demonstrates that mobile channels fundamentally alter the customer's search process by offering better information accessibility compared to traditional online channels. These differences in search behavior result in a larger consideration set while searching for products, and then lower return rates for purchases made on mobile channels. Moreover, mobile channel utilization reduces the unique effect of discount promotions on return behavior, suggesting that channel utilization is a dominant antecedent and moderator of return behavior. With respect to the consequences of these returns, drawing on customer learning literature and attribution theory this research demonstrates that returns can both help and hurt a firm's future customer relationships, contingent on category characteristics. Specifically, we find that in categories where the return process can contribute to product learning that can be leveraged in the future (Anderson and Simester 2013) returns will positively affect future purchases. However, if customers cannot easily leverage the learned experience in the future, the opposite pattern emerges. These results

[7] In mobile channels, customers can shop using smart phones that have mobile applications and mobile web browsers. In traditional online channels, customers shop using desktops, laptops, or tablets. To connect to the internet, these traditional online channels often require a Wi-Fi environment. This classification is based on the level of the devices' portability.

suggest that strategies that target channel utilization across categories can result in significant cost savings related to initial product returns and increase future spending following the occasional return incidence.

In what follows, we first discuss the literature and theories related to product return and the consumer decision-making process. We then develop the hypotheses, describe the studies, and discuss the findings. Lastly, we draw conclusions and address the caveats and future research.

Literature and Theory

Product Returns

Product returns constitute a critical element in the marketing exchange process yet have received relatively little investigation in the marketing literature compared to the other exchange elements of buying behavior and marketing communications (Petersen and Kumar 2009). Given the critical role of the return process in restoring customer satisfaction with a retailer, most marketing research has focused on better understanding consumer reactions to return policies and how this can drive future loyalty (Bernon, Cullen, and Gorst 2016; Petersen and Kumar 2009). These investigations have demonstrated that liberal return policies boost return rates substantially (Bower and Maxham 2012; Wood 2001). On the other hand, if returns are at the customer's expense, the customer is less likely to return products (Anderson et al. 2009; Bower and Maxham 2012), but this strategy adversely affects the customer's future purchase intention and long-term profitability (cf. Petersen and Kumar 2015).

Noticeably missing from these investigations is a better understanding of the key drivers of product returns and how they can be better managed proactively. Prior research has demonstrated that the desire to return a product is triggered when buyers experience remorse and cognitive dissonance, and these emotionally-charged evaluations outweigh rationale assessments of product quality and damaged goods (Lawton 2008; Powers and Jack 2013; 2015). However, the decision to return a product represents a critical post-purchase moment of truth that has not been deeply investigated, understood or aligned with today's online buyer behavior.

Even less academic research has been conducted to learn the consequences of product returns. Petersen and Kumar's series of product return research (2009, 2011, 2015) finds that a certain level of return rate can actually boost a firm's bottom line due to the decrease of perceived risk by the customer. However, research is still needed to understand product returns as a double-edged sword in a much more refined sense, such as under what circumstances they render benefits to companies.

In terms of context, extant research focuses on catalog, in-store, and e-commerce retail (i.e., Ofek et al. 2011; Wood 2001). However, as indicated, as prevalent as e-tailers and online shopping are nowadays, further dissecting the online channel itself which contains both the traditional online channel and mobile channel, can provide insightful guidance to many businesses in relation to their marketing strategies. Table 1 summarizes prior studies in terms of the *antecedents* and *consequences* of product returns along with their research contexts. It also delineates the scope of our study relative to those studies.

Insert Table 1 about here

Information Search and Decision Making in Digital Channels

To close the above discussed research gaps, we assess how the consumer decision-making process can directly affect product return behavior by leveraging theories of information search and assimilation. In doing so, we demonstrate the general process by which search can directly impact return rates and how these search behaviors vary across channels.

Since the late 1990s, marketing researchers have highlighted the differences in consumer decision-making and behavior across online and traditional retailing (Alba et al. 1997). Through these investigations, it has been demonstrated that fundamental structural differences and requirements in the channel can shift the evaluation process and cause consumers to focus on different aspects of the decision and access and use information differently (Alba et al. 1997; Huang, Lurie, and Mitra 2009; McKinney, Yoon, and Zahedi 2002). A theme that recurs through these investigations is the critical importance of information provision during the shopping experience. Alba et al. (1997) noted that traditional offline channels offer much richer information access during the evaluation of alternative phases than traditional online channels, which can result in consumers having lower overall satisfaction and confidence in their decisions when using digital channels unless the experience is improved. Extending this research to the latest channel evolution requires an assessment of the fundamental differences between mobile and traditional online channels.

While both channels are digital (mobile and the traditional online "computer" channels), there are fundamental structural differences in how, when, and where consumers can access information and make purchases between these channels which can alter their behavior and decision making (Ansari, Mela, and Neslin 2008; Verhoef, Neslin, and Vroomen 2007). One of the most prominent differences between mobile and traditional online channels is the information benefits for customers (Larivière et al. 2013; Wang, Malthouse, and Krishnamurthi 2015). Specifically, mobile channels provide an opportunity to potentially access and share information more easily than traditional online channels, and this improved information accessibility can spill over and alter the decision-making process and ultimately the post-purchase product evaluation.

Information Theory and Consumer Evaluations of Purchase Decisions

The conceptual model in this research is rooted in two complimentary theoretical streams related to information processing and search. In line with information theory (Shannon and Weaver 1949), we contend that consumers make better decisions as more information is made available to them during the decision-making process, and the simple process of searching for information can inflate evaluations of purchases (Cardozo 1965). Next, we dive deeper into these theoretical anchors. Information theory (Shannon and Weaver 1949) suggests that accessing better quality information can increase the likelihood of making an objectively higher quality purchase decision, which limits future regret and dissonance (Keller and Staelin 1987; Chen, Shand, and Kao 2009). Independent of the objective decision quality, the simple process of exhaustively searching for information can inflate future product evaluations through assimilation, where the consumer feels compelled to ensure their product evaluation matches their effort (Alba et al. 1997; Anderson 1973; Cardozo 1965).

Both of these processes unfold as consumers engage in active decision-making. Specifically, after consumers experience a need, they begin the purchase process and search for information internally and externally to increase their chances of best satisfying their focal need (Bettman 1970). During this process, the more relevant information a consumer can gather and process, the more confident they will be in their decision (Keller and Staelin 1987). These early investigations into the role of information search and evaluation were conducted in offline contexts, but more recent research has confirmed their applicability to digital channels as well. Specifically, McKinney, Yoon, and Zahedi (2002) demonstrate that as information quality increases, consumers are more likely to experience satisfaction as a more informed choice has a higher likelihood of confirming a buyers' expectations (Szymanski and Hise 2000). Thus, the ability of a digital channel to provide information directly to a consumer can lead to better decisions, and logically spillover to lower returns.

In addition to simply improving the quality of the decision, the information search process can also directly impact the emotional assessments of a purchase decision. Specifically, Anderson (1973; p. 43) notes that “the mere processing of information may lead to a more favorable evaluation of the product, not only because customers have greater knowledge on which to base evaluation, but also because processing of information about the products constitutes a form of commitment to the products.” These effects are posited to hold when the differences between expectations and performance land within the zone of tolerance at which point a consumer will inflate their evaluation of the product to confirm their pre-purchase expectations (Anderson 1973). In these instances, the more extensive the search and integration of information, the more satisfied a consumer would be with the outcome of the purchasing process.

These assimilation effects assume that information is received from various sources. In a digital context these sources can include the website directly, associated promotions, consumer reviews, and even opinions directly solicited by the consumer from individuals who they know and trust (Alba et al. 1997). Specifically, digital channels remove the co-location criterion for group shopping and information sharing and provide a mechanism for consumers to get real-time or delayed feedback on an impending purchase. Supplementing information from a retailer, manufacturer, and other anonymous users with the subjective norms of a peer group can further bolster consumer confidence in the purchase decision. This additional process reinforces both mechanisms by which information can impact product evaluations, because consumers can access more information that should lead to an objectively better decision, and the simple process of the search and assimilation of information can directly bolster satisfaction with the decision, in parallel. Moreover, in an e-commerce context, customers' search can involve both depth (time per page) and breadth (number of pages) and this search process is extensive in online channels (Huang, Lurie, and Mitra 2009). In general, increases in information search can lead to higher information quality and ultimately better decisions and satisfaction (McKinney, Yoon, and Zahedi 2002). Given the dominant role of the information search process across a number of channels, any variance in this process due to the channel will spillover and impact consumer evaluations and ultimately return frequency.

Hypothesis

Antecedent of Product Returns: Channel Utilization (Mobile versus Traditional Online Channels)

The e-commerce literature suggests that the two sub-channels of online shopping (i.e., traditional online channels and mobile channels) have differential information benefits for customers (Larivière et al. 2013; Wang et al. 2015). A core difference between the channels is the type and amount of information search available and how this information is used. On the one hand, mobile channels empower customers more than the computer-interface channels (traditional online channels) by giving them the ability to access information on the spot from multiple sources, compare product prices, and obtain relevant promotion information in a timely manner (Joy et al. 2009; Kim, Wang, and Malthouse 2015; Wang et al. 2015). Importantly, mobile shopping is more than just accessing web pages on a mobile device. Larivière et al. (2013) and Shankar, O'Driscoll, and Reibstein (2003) suggest that, due to their mobility, mobile channels can satisfy customers' consumption goals more economically than other channels.

Research on mobile channels suggests that they are more convenient and can provide more accessible information than traditional online channels (Balasubramanian, Peterson, and Jarvenpaa 2002; Lai, Debbama, and Ulhas 2012; Larivière et al. 2013; Wang et al. 2015). These two features are made possible by the mobile phone's portability and functionality (Lai et al. 2012), which allow consumers to access product information during both non-shopping times and during the purchase experience (Daurer et al. 2015). Moreover, mobile users can easily capture and share product information with other opinion leaders via texting and social media platforms in a much more seamless setting compared to traditional online outlets to get a second opinion. The consumer survey cited earlier confirms this. Among the 156 respondents, 62% affirmed that before they purchased a product, they had sent a picture of the product or the link to the product to their friends or family, something more easily done while mobile shopping.

This extended access to information from various sources and ease of starting and stopping the information search and assimilation process allows mobile shoppers to extend the purchasing process and acquire more information. This extended information search can result in a larger consideration set of products that a consumer would consider buying in the near future (Robert and Lattin 1991). In instances with extensive information search, the consideration set tends to increase in size, which gives the consumer more options to evaluate (Sambandam and Lord 1995). Our data indicates that the consideration set formed while customers shop on the mobile channel is 162% larger compared to that formed while customers shop via traditional online channels.[8] As the number of alternatives evaluated increases, customers become more

[8] We follow Moe (2006) and Naik and Peters (2009) and utilize the number of products browsed in the store as the proxy for the consideration set. Sample A's store level data indicate that the average number of items a customer viewed on the mobile channel is significantly larger than that on the traditional online channel (M_{mobile} = 5.90, $M_{traditional\ online}$ = 2.25, t-value = 83.89, $p < .001$). Therefore, the assertion that customers establish larger consideration sets and conduct more information searches on mobile channels than on traditional online channels is supported by our empirical data. Similar results are found in the 2016 Criteo mobile commerce report in the United States.

informed while making purchase decisions (Borst and Theunissen 1999; Klir and Wierman 1999). This suggests mobile channels yield valuable and instant product information to customers whenever needed and also give customers opportunities to evaluate more options. As such, given mobile channels' superior access to extensive product information, the ability to extend the evaluation process outside of the focal shopping window, and to more easily share product ideas with opinion leaders and assimilate their opinions, we propose:

> H_1: Mobile channel utilization is negatively associated with product returns, as compared to traditional online channel utilization.

Moderating Role of Channel Utilization on Discount Promotion

In addition to the main effects of channel utilization, we propose that the utilization of a mobile versus traditional online channel will alter the effect of discount promotions in e-commerce. This moderating role is rooted in the theoretical notion that firms display their promotions to customers via various channels and differences between channels may alter the impact of this information on return propensity. The same information, depending on how it is presented and subsequently how it is decoded by audiences, may generate differential influences.

We consider discount promotion information because it is a strong driver of returns (Petersen and Kumar 2009) and often utilized in retail. Discount promotions are useful cues for customers that aid in cognitive evaluations of products and purchase decisions (Raghubir 2004). Intense promotional events have the potential to inflate impulsive shopping behavior (Kau et al. 2003). Such impulsive shopping often adheres little to rational and coherent thinking (Beunza and Stark 2012), and can yield inaccurate perceptions of the product and its associated utility during a purchase. This leads to more discrepancies, and consequently more remorse, cognitive dissonance, and product returns.[9]

While promotions can traditionally erode the quality of decision making, this effect is contingent on the extent to which the promotion is the primary information processed versus other informative cues that the consumer gathers from the environment. When utilizing a mobile channel, information is more accessible to consumers from a broader array of marketing and non-marketing controlled information sources (i.e., view more alternatives or share potential products with opinion leaders). These increases in information availability can weaken the direct effect of promotions relative to traditional, online channels. In other words, when customers are armed with additional information in the decision-making process, the relative weight of the promotion is discounted and its effectiveness is reduced. Specifically, increased search can reduce the effects of promotions on a subset of products and, instead, consumers will form a more exhaustive set of purchase alternatives, which results in better decision making and satisfaction, which reduces returns. Thus, we hypothesize that:

> H_2: Mobile channel utilization moderates the relationship between discount promotion and product returns, such that the relationship is weakened (i.e., less positive) when purchases are made through mobile channels rather than traditional online channels.

Consequences of Product Returns

The product return literature overwhelmingly focuses on the costs of product returns (i.e., Anderson et al. 2009; Bower and Maxham 2012). However, in a series of product return papers, Petersen and Kumar (2009, 2010, 2015) demonstrate that customers who process returns for a reasonable number of purchases are more profitable to the firm. The premise is that return

[9] Given the well-established effects of how promotions are processed and could impact consumer behavior, we do not formally propose the main effect, but rather include it as a control in the analysis.

behaviors can lower customers' perceived risk of current and future purchases. Taken together, the results are mixed with some evidence pointing to the negative consequences associated with returns and others touting longer-term, relational benefits. Given the conflicting arguments in the literature, part of our research involves uncovering a more complete picture of product returns' consequences by contributing to the evidence on *when* returns are good or bad for the firm.

To provide new insight into when returns could potentially help or harm future business, we examine the extent to which category differences can alter the effect of product returns on future behavior. Specifically, we utilize the perspective from consumer learning (Anderson and Simester 2013) to explain why in easy-to-learn contexts, returns can facilitate future business, but in categories that are hard-to-learn, returns can have a negative effect. The basis for this integration is the theoretical notion that a customer's product return experience represents a key, post-purchase experience (Lemon and Verhoef 2016), where the customer can learn more about the products and brands from which they recently purchased (Anderson and Simester 2013; Petersen and Kumar 2009). During these instances, customers glean new insights into the brand and can either be forward-looking by leveraging the return experience to gain new knowledge that will make them more effective consumers in the future, or look back retrospectively and simply focus on the failed purchase experience. As a consequence, building on the work of Anderson and Simester (2013), we contend that product category characteristics can impact the ability of customers to learn from their experiences and, in a dual option mode, customers can improve their decision making in the future or they can simply disengage from the learning process and focus on prior failed outcomes.

The process guiding these behavioral changes can be explained by the elements of attribution theory, which suggests that after experiencing a failed product purchase and processing a return, a customer will make attributions about the outcome and ask "why" did this happen and "if" it is likely to occur in the future (Wong and Weiner 1981). Specifically, customers will assess whether this type of failed outcome is stable or is likely to occur in the future or they can learn from it and alter future outcomes. If they think the failure is stable, then they will likely avoid similar experiences in the future (Weiner 1995; Weiner 2000). Thus, in a context where the consumer has high learning barriers, the likelihood of experiencing a similar fate in the future is high, thus consumers will reduce/avoid future purchases. In categories where learning is easier, consumers can adjust their expectations and purchase selections and, thus, future failed outcomes are less stable and consumers will be more likely to engage in repeat purchases. Ultimately, if customers can learn from the purchase process and associated return experience, they will feel as if they have more control over future outcomes and are more likely to be motivated to try again (Rotter 1966).

In the context of our research (apparel), purchases from categories where adults directly purchase products for personal use (e.g., women's apparel) have been demonstrated to be a context conducive to learning. However, in a context where consumers are purchasing products for someone else (e.g., children's apparel), learning is more difficult (Anderson and Simester 2013). The logic for these learning differences is straightforward: purchasing children's apparel is a context where learning from an experience is more challenging as buyers must process a much higher number of variables (i.e., children's preferences and children's changing sizes) and integrate this knowledge into the experience. Also, children's sizes are prone to variation and change frequently and, importantly, sizes and product fit are the primary reason for customers returning their online purchases (Anderson and Simester 2013). Alternatively, in women's apparel, sizing for the customer is more stable and customers who know their own tastes and preferences purchase products for their own use. Hence, they can take control of future purchases and be more likely to experience a more successful outcome. Thus, we propose:

> H_3: Customer's learning difficulty moderates the relationship between product returns and future purchases, such that when product categories are easy to learn, product returns enhance future purchases; when product categories are difficult to learn, product returns reduce future purchases.

Study 1: Antecedents of Product Returns

Data and Variables

To examine the antecedents of product returns with a focus on channel utilization, we collaborated with two companies which have been ranked number one in their respective sub-categories in the apparel industry by Alibaba in terms of annual sales. Both companies are online-sale only companies (e-tailers). As such, they have two digital channels available to sell products to their customers: mobile channels and traditional online channels. Company A (Sample A) sells women's apparel while company B (Sample B) sells children's apparel. We opted to study the apparel industry since product returns in this industry are rather severe with the highest return rate of 30-40 % (Reagan 2019), making the industry context very relevant for our research focus on product returns. Also, obtaining datasets from different sub-categories of the apparel industry and two different companies add generalizability to the findings. To attain comparable results, all variables are operationalized in a consistent fashion across samples (see operationalization details in Table 2).

In addition to the variables of interest (channel utilization and discount promotion), we also control for the focal order's characteristics such as total spending, average item price, whether the order was placed during holidays, and the recentness of the order, all of which are deemed to be drivers of returns as well according to the literature (i.e, Petersen and Kumar

2009). Company A offers free shipping on all purchases, while company B charges shipping fees based on the customer's location and spending. Thus, the analyses of Sample B also include shipping fee as an additional covariate.

Insert Table 2 about here

Empirical Challenges: 1) Switching Channels between Searching and Purchasing Products

Without proper controls, it could be possible that the results could be biased based on cross-channel shopping behaviors of consumers. We proactively addressed this potential issue in two ways. First, the two firms included in our studies are etail-only operations, so they do not offer customers the ability to browse or review products offline. By selecting these firms, we limit all shopping experiences to traditional, online or mobile channels. Second, we reduced this risk apriori with sample selection rules that would make this phenomena very unlikely in our data. Specifically, we only included customers who exclusively purchased in either the traditional or mobile channel during the study period for our main analyses from both Sample A and Sample B. We conjecture that customers who only purchase on one channel are more likely to search exclusively on that channel as well, compared to those who purchase on multiple channels. Using these sub-samples instead of the entire samples adds more credibility to our contentions. Collectively, these efforts provide a clean and valid sample for assessing the effect of the channel on product return behaviors. .

Empirical Challenges: 2) Endogenous Selection Bias of Channel Utilization

Another challenge of the channel utilization variable is self-selection bias that can potentially distort the parameter estimates. Explicitly, whether customers opt to use mobile channels or traditional, online channels while shopping is subject to self-selections. Without removing this bias, results of the relationship between channel utilization and returns may stem from customers' heterogeneity rather than different channel features. To enhance rigor and ability to infer causality, we employ the propensity score matching (PSM) method to form two matched samples (one for each sample[10]) following the steps of Iacus, King, and Porro (2012) and Wang et al. (2015). Specifically, we select a treatment group of customers who only purchased on mobile channels during the post-study period and have characteristics (shown in Appendix A1) similar to the control group of customers. The customers in the control group only purchased on traditional online channels. According to the channel literature (i.e., Wang et al. 2015), we assert that these characteristics in Appendix A1 (customers' shopping behavior during the pre-study period and demographic characteristics) are determinants of the likelihood of a customer using a mobile channel or traditional online channel. The assumption is that two customers with similar propensity scores (difference <.0000005) have a similar likelihood of being assigned to the treatment group (i.e., using mobile channel). In reality, one used a mobile channel (i.e., in the treatment group) and the other didn't (i.e., in the control group). Namely, the only difference between customers in a matched sample is whether they have chosen to use different channels. Then, we select all purchases of these matched customers' during the post-study period. We also ensure that these matched customers at least purchase two orders during the post-study period to render a panel data structure, which can help eliminate more confounding factors. Finally, using these panel datasets, one for each sample, we test the impact of channel utilization on return percentage (the percentage of items of an order that was returned) during the post-study period.

[10] Sample A's pre-study time period is January to September 2014, and its post-study period is October to Dec 2014. Sample B's pre-study period is January to June 2015, and its post-study period is July to December 2015.

Empirical Challenges: 3) Endogeneity of Discount Promotion

Discount promotion may also be leveraged in a strategic manner by retailers, making it potentially endogenous. In this research, we control for potential endogeneity using the Gaussian Copula method (Park and Gupta 2012) which does not require instrumental variables. It is extremely helpful when valid instruments are hard to find (Rossi 2014) as this method is able to directly model the joint distribution of the endogenous regressors and the error term. One critical requirement of this method is that endogenous variables are not normally distributed. Using Shapiro-Wilk tests, we find that discount promotion is not normally distributed (Sample A, W = .907, p < .001; Sample B, W = .984, p < .001). Following Park and Gupta (2012), we add the following regressor (in Equation 1) in the tested models (see Equation 4):

$$Copula_{discount_{ij}} = \Phi^{-1}\left(H_d\left(discount_{ij}\right)\right) \qquad (1)$$

where $\Phi^{-1}$is the inverse of the normal cumulative distribution function (CDF), and $H_d(\bullet)$ is the empirical CDF of discount promotion.

Analyses and Results

The original datasets to create the matched samples discussed above contain 65,523 customers (35.4% used mobile channels) from Sample A and 50,761 customers (80.4% used mobile channels) from Sample B. First, using a logit regression, we model the relationship between covariates in Appendix A1 and whether a customer utilized a mobile channel for Sample A and Sample B. The probability that customer *i* utilized a mobile channel is shown in Equation 2:

$$P_i = \Pr(CU_i = 1 | \ln(\boldsymbol{v_i} + 1),\ \boldsymbol{d_i}) \qquad (2)$$

where CU_i is a binary variable that indicates whether customer *i* utilized a mobile channel exclusively during the post-study period, vector $\boldsymbol{v_i}$ contains customers' prior shopping behavior covariates, and vector $\boldsymbol{d_i}$ contains demographic covariates. The logit regression (shown in Equation 3) assigns the propensity score $\widehat{P_i}$ to each customer:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \boldsymbol{d_i}\lambda_1' + \ln(\boldsymbol{v_i}+1)\,\lambda_2' + \varepsilon_i \qquad (3)$$

where λ_1' and λ_2' are the unknown parameter vectors for demographic covariates and behavioral covariates, respectively, and ε_i is the random error.

The results of the logit regression are presented in Appendix A2. We utilize 1:1 matching and the nearest-neighbor matching algorithm to create the matched samples (8,848 for Sample A; 14,336 for Sample B). To demonstrate covariate balance after matching, as suggested by Imbens and Rubin (2015), we compute and contrast the normalized difference in means (ND_j) for each covariate *j*. The comparisons of the NDs before and after matching are shown in Appendix A1. We find that after matching nearly all NDs are reduced, which indicates an improvement in balance.

After selecting matching customers, we form a panel dataset for each sample, containing all orders customers purchased during the post study period (at least two orders per customer). Table 3 and 4 contain summary statistics and correlations of all variables used in the main analyses for Sample A and B, respectively.

Insert Table 3 and 4 about here

Then, we conduct tests using a random effect model with clustered robust standard errors (at the customer level). As stated, to prepare the panel datasets we only selected the samples to customers who placed at least two orders during the post study period, resulting in two analyzed datasets that contain 21,030 orders placed by 8,848 customers for Sample A and 36,221 orders placed by 14,336 customers for Sample B. We also control the propensity score of each customer as suggested by Wang et al. (2015) in the tested model. The full model is shown in Equation 4.

$$Return\_percent_{ij} = \beta_0 + \beta_1 discount_{ij} + \beta_2 CU_i$$
$$+\beta_3 CU_i * discount_{ij} + \beta_4 totalspending_{ij} + \beta_5 price_{ij} + \beta_6 recency_{ij} +$$
$$\beta_7 holiday_{ij} + \gamma_1 pscore + \gamma_2 Copula_{discount_{ij}} + \varepsilon_{ij} \qquad (4)$$[11]

where $Return\_percent_{ij}$ is the percentage of order j's items that was returned, $discount_{ij}$ is discount promotion, CU_i is a binary variable that indicates whether customer *i* used a mobile channel, pscore is the propensity score we received from the PSM step earlier, and the random errors ε_{ij} (see details of all variables in Table 2).

Sample A Results: Table 5 demonstrates that channel utilization has a direct and negative impact on product returns ($b = -.004$, $p < .001$). These results support the notion that orders placed on mobile channels are less likely to be returned as compared to those placed on traditional, online channels, which is consistent with H_1. The statistical significance of the interaction coefficient between the channel utilization and discount promotion ($b = -.043$, $p < .05$) suggests that the channel utilization weakens (i.e., less positive) the relationship between discount promotion and product returns. A one standard deviation increase in discount promotion increases the return percentage of a mobile order to a lesser extent than a traditional online order. Thus, H_2 is supported.

Insert Table 5 about here

Sample B Results: Table 5 also reveals that the channel utilization has a direct and negative impact on product returns ($b = -.007$, $p < .10$), which suggests that orders placed on mobile channels are less likely to be returned, as compared to those placed on traditional, online channels, in accordance with H_1. The interaction coefficient between the channel utilization and discount promotion ($b = -.001$, $p < .001$) is significant, thus H_2 is supported in Sample B.

[11] Sample B's model has an additional covariate which is shipping fee.

Overall, Sample A and B deliver largely consistent results for the tested hypotheses, suggesting the generalizability of our findings.

Robustness Checks (RC)

In addition to using two samples from two different retailers and finding consistent results of our tested hypotheses, we also implement two robustness checks to further rule out alternative explanations.

RC1, channel utilization does not impact products purchased: To exclude the explanation that channel utilization impacts the type of products purchased, we compare the sales across the two channels for the same products (SKUs). There are 6,627 unique SKUs in Sample A. The paired samples t-test reveals that the differences in product sales for a certain product during October 2014 to March 2015 across two channels are not significant ($Mean_{mobile} = 234.99$, $Mean_{traditional} = 231.01 t_{paired} = -1.373$, $p = .170$), but as our main results demonstrate, there is a significant difference in the total number of returns given a constant number of sales across the two channels studied. Thus, we are confident that this alternative explanation is effectively eliminated. In addition, we intend to further demonstrate that the search volume for the same products (SKUs) is higher on mobile channels than traditional online channels. The paired sample t-test shows that the search volume (consideration set) conducted on the mobile channel for a certain product is significantly higher than that on the traditional online channel ($Mean_{mobile} = 7.01$, $Mean_{traditional} = 3.07$; $t_{paired} = 316.82$, $p < .001$)[12]. Thus, we conclude that customers search more on mobile channels than traditional online channels, which affects their decision quality

[12] To conduct this test, we focused on orders where only a single product was purchased. This allowed us to compare search differences with a controlled purchase outcome that could be held constant across the sub-channels. By adding this constraint, our data was reduced to 3,115 unique SKUs.

and thus return tendency, but does not affect their overall purchase volume for a certain product. In other words, channel utilization does not impact the type of products purchased.

Another test we conduct to further support our contention is to use the aggregated store-level daily data for the year 2014 regarding store sales, number of customers, number of products sold, and number of page views across two channels. Specifically, we first calculate the percentage of sales accomplished on the mobile channel at a daily level and split the data into two sub-samples: (1) days with mobile sales lower than or equal to average (sample 1 contains 167 days) and (2) days with mobile sales higher than average (sample 2 contains 194 days). Then, we conduct an independent sample t-test across these two datasets on the sum of store sales, sum of customers, sum of products sold, and sum of page views of the two channels. The results show that there are no significant differences in all variables across the two datasets, except the sum of page views, supporting our contention that customers search more on mobile channels than traditional online channels. Also, this increased search does not affect their overall purchase volume (Msales sample1 = 1,769,957, Msales sample2 = 2,138,013, t = -.35; Mcustomer sample1 = 10,107, Mcustomer sample2 = 9,744, t = .09; Mproduct sample1 = 16,921, Mproduct sample2 = 15,558, t = .19; Mview sample1 = 4,394,012, Mview sample2 = 5,948,930, t = -2.54).

RC2, various forms of dependent variables: In the main analyses, return percentage (ratio of the number of items returned to the total number of items purchased for an order) is the dependent variable (DV). To test the reliability of our findings, we also construct a dummy DV which is whether an order is returned or not (as long as one item got returned, we assign 1 to that order, otherwise 0). The third DV is formed as a count variable - the number of items returned for an order. We then run multi-level logit and multi-level poisson models along with the same explanatory variables as in the main analyses, but using the two newly-developed DVs, respectively. The results are shown in Table 6. The consistent findings revealed in this robustness check add reliability and validity to our main results.

Insert Table 6 about here

Discussion

The first study demonstrates that product returns are contingent on the choice of digital shopping channel. Specifically, consumers who used mobile channels appear to make better decisions, thus return products less frequently. Moreover, in addition to the direct effects, mobile channels can also alter the effect of discount promotions. Specifically, discount promotions have weaker effects on returns in mobile channels versus traditional online channels. In sum, these results demonstrate that consumer channel choice is an important antecedent of return behavior. In an effort to extend these results and provide a comprehensive assessment of returns in an e-commerce study, we now discuss our second study that examines the consequences of product returns.

Study 2: Consequences of Product Returns

To test the impact of product returns on consumers' future purchases, we need to remove the endogenous selection bias of returns, construct the return experience as a random treatment, and examine its causal impact on future purchases. To do so, we also employ the PSM method to form two matched samples (one for Sample A and one for Sample B[13]) following the steps in Study 1. Specifically, we select a treatment group of customers who returned their first orders ($order_j$) during the post-study period and have characteristics (shown in Appendix A3) similar to

[13] Sample A's pre-study time period is October 2014 to December 2014, and its post-study period is January 2015 to March 2015. Sample B's pre-study period is January 2015 to June 2015, and its post-study period is July 2015 to December 2015.

the control group of customers. The customers in the control group did not return their order_j. According to the return literature and Study 1, we assert that these characteristics in Appendix A3 (customers' shopping behavior during the pre-study period, order_j characteristics, and demographic characteristics) are determinants of the likelihood of an order_j being returned. Thus, the only difference between customers in a matched sample is whether they have returned the order_j. Using these matched samples, we test the impact of product returns (whether order_j was returned) on purchase amount (dollar value) of order_{j+1} (the second order they purchased during the post-study period). Customers included in Study 2 need to purchase at least three times: one is in the pre-study period and two are in the post-study period.

The original datasets to create the matched samples contain 51,962 customers (2.39% returned order_j) from Sample A and 58,812 customers (12.52% returned order_j) from Sample B. First, using a logit regression, we model the relationship between covariates in Appendix A3 and whether a customer returned an order_j for Sample A and Sample B. The probability that customer *i* returned their order_j is shown in Equation 5:

$$P_i = \Pr(return_i = 1 | \ln(\boldsymbol{v_i} + 1),\ \boldsymbol{d_i}, \boldsymbol{order}_j) \qquad (5)$$

where $return_i$ is a binary variable that indicates whether customer *i* returned his first order in the post-study period, vector $\boldsymbol{v_i}$ contains customers' prior shopping behavior covariates, vector $\boldsymbol{d_i}$ contains demographic covariates, and vector $\boldsymbol{order}_j$ contains order_j's characteristics. The logit regression (shown in Equation 6) assigns the propensity score $\widehat{P_i}$ to each customer:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \boldsymbol{d_i}\lambda_1' + \ln(\boldsymbol{v_i}+1)\ \lambda_2' + \boldsymbol{order_j}\lambda_3' + \varepsilon_i \qquad (6)$$

where λ_1', λ_2', and λ_3', are the unknown parameter vectors for demographic covariates, behavioral covariates, and order_j's characteristics, respectively, and ε_i is the random error.

The results of the logit regression are presented in Appendix A4. As in Study 1, we utilize 1:1 matching and the nearest-neighbor matching algorithm to create the matched samples (2,224 for Sample A; 9,006 for Sample B). To demonstrate covariate balance after matching, we also compute and contrast the ND_j for each covariate j. The comparisons of the NDs before and after matching are shown in Appendix A3. We find that after matching nearly all NDs are reduced, which indicates an improvement in balance. The summary statistics and correlations of variables in the matched samples are shown in Table 7.

To test H_3, we employ two generalized linear models to examine the impacts of product returns on customers' future purchases across product categories with various levels of customer learning difficulty. We also control the propensity score and the characteristics of $order_{j+1}$ (shown in Table 7) in the final model. The results shown in Table 8 indicate that return experiences significantly increase customers' future purchases ($b = 1.020$, $p < .001$) in Sample A (i.e., the low customer learning difficulty category). However, return experiences significantly decrease customers' future purchases ($b = -.057$, $p < .001$) in Sample B (i.e., the high customer learning difficulty category). Taken together, overall, we find support for H_3. We also analyzed the model with order size (the number of items purchased for an order) instead of purchase amount as the DV and received consistent findings to those in Table 8.

Insert Tables 7 and 8 about here

General Discussion

Our research takes a significant step toward better understanding the difference between what firms know and practice today in online shopping regarding product returns, and what firms clearly need to know about mobile and traditional online channels' roles in driving returns and how customer learning adjusts the impact of returns on customers' future purchases. Next, we discuss the implications of our findings for both managers and researchers.

What Firms Can Do?

How can channel coordination strategies be optimized in e-commerce? The results of the first study suggest that customers are more satisfied with purchases through mobile channels and they return the products less. Coupling these results with robustness check 1 (*RC1*) that demonstrated comparable overall purchase volume across the two channels, we suggest that firms could improve customer relationships by developing strategies to shift customer shopping behavior to the mobile channel. In reality, some firms like Myntra (the largest online fashion store in India) have already increased investment in mobile and are experimenting to find the right balance between mobile and traditional online channels. Similarly, retailers like Macy's and Hotel.com offer mobile-only promotions to entice shoppers to switch to this digital sub-channel.

Our results further suggest that all retailers should have a deliberate policy planning discussion about coordinating their channel strategies. Specifically, firms should acknowledge that mobile channels and traditional online channels function differently in terms of providing customer information search experiences and, ultimately, customer conversion. Given their unique features, we suggest that instead of selecting one channel over the other, firms need to synchronize the two sub-channels to maximize effectiveness in managing returns. In this online synchronization era we are entering, optimizing across online channels with respect to what drives product returns or not should be a strategic initiative that firms undertake.

One tactic to try and leverage the differential performance of the two sub-channels would be to target and entice customers who have a high return rate to use mobile channels, such as launching exclusive mobile promotion events and/or sending mobile notifications to those customers, to reduce their likelihood of making a return. Our results also suggest that for heavily promoted products, firms may consider displaying them on mobile channels exclusively to decrease return rates.

What can traditional, online channels learn from mobile channels? Although we find that mobile channels can reduce return rates, as compared to traditional online channels, many customers still prefer to use the traditional online channel due to its unique features. Additionally, many companies' e-commerce business relies heavily on traditional online channels (in many cases due to resource constraints in implementing effective mobile options). To cope with this situation, we suggest that traditional online channels need to incorporate, as much as possible, the convenience and high accessibility of information that sets mobile channels apart from traditional online channels. In other words, traditional online channels could benefit from aiding customers to develop larger consideration sets while shopping. For example, when a customer searches for a product on Amazon.com, Amazon recommends "frequently bought together," "sponsored products related to this item," and "customers who bought this item also bought". All these efforts are intended to encourage customers to conduct a more extensive information search, thus establishing a larger consideration set, and ultimately confirming the customers' expectations following purchase. Also, adding a function that can facilitate customers to send product links and pictures to others easily from the website can further assure customer purchase. As a result, customers are less likely to return the products purchased. Firms are wise to adjust the design of their traditional online channels by, for example, facilitating the shopping process for customers.

Are returns good or bad? At the outset, firms incur additional operating expenses when a customer processes a product return. These return costs can be so extensive that some e-commerce executives have called them ticking time bombs (Dennis 2018), thus questioning the long-term sustainability of liberal return policies. However, our results verify and extend prior research that suggests these costs are not incurred without a benefit (e.g., Peterson and Kumar 2009). Specifically, our results suggest that in categories with low learning barriers, such that customers can easily learn the attributes of a product from their return instances, a return experience can directly lead to future sales. For product categories that require little learning from customers and where customers can leverage their return experiences easily in their future purchases, retailers actually benefit from returns through increased patronage. Thus, a high return rate is not as troublesome in these cases as it is in situations where product categories require significant learning and customers are not likely to reflect on their return experiences in future shopping. Our results suggest that the value of returns is complex and can be greatly contingent on category characteristics. Thus, managers need to assess the impact of returns on future purchases across their categories and, in addition, should consider examining differences in the return and future spending relationship across segments.

Avenues for Future Research

In addition to the managerial implications, our research provides fresh theoretical and research avenues in the areas of product returns, e-commerce, and channel literature. First, given the strategic importance of product returns, particularly for e-tailers' operations, more research is needed into how firms can try to proactively influence their return rates without damaging customer relationships (e.g., Petersen and Kumar 2009). Initial research in this area has highlighted the impact of extreme variations in return policies but stopped short of assessing the true financial impact of different approaches for handling returns with customers. Moreover, much of the research on returns has generalized across channels or simply focused on in-store and online channels (see Table 1). However, our results suggest that important nuances in customer behaviors could be overlooked with these approaches. Specifically, we take a deeper dive into examining the differences in channel utilization in e-commerce (mobile vs. traditional online channels, the two most frequently used online channels by consumers). We find that channel utilization is not only a driver of return behavior but also weakens the effect of another important driver of returns: discount promotions. More importantly, we articulate that it is mobile channels' ability to facilitate more information search, assimilate customers' opinions and extend the evaluation process outside of the focal shopping window, and functionality to share product ideas with opinion leaders that lead to fewer returns. Unfortunately, we do not possess individual-level information of these variables to empirically test our arguments. Future research can build on our theoretical contentions and test the mechanisms discussed above.

To advance the e-commerce literature stream, given the dual roles of the marketing channels (outbound and inbound), we show that channel coordination in online contexts could be a remedy for managers to reduce return rates in e-commerce. Our results suggest that extensions might be needed on a multichannel strategy. Most multichannel research stresses channel coordination between online and offline channels (i.e., Bell, Gallino, and Moreno 2015; Gensler, Neslin, and Verhoef 2017), with limited distinction between variations in digital channels. Our results highlight differences across two digital sub-channels and suggest that we can no longer consider multi-channel research to be as simple as brick-and-mortar versus digital. Thus, potential differences across newly emerged channels should spur more academic studies that can put forward many interesting ideas.

Finally, our research contributes to the ongoing dialogue on the benefits and costs of product returns, answering calls for research that evaluates the consequences of returns. Our research articulates that returns can be both good and bad depending on categories of products that are returned by customers. Return experiences represent one type of learning that customers employ to study brands and products in order to make a more accurate purchase decision the next time. However, for some product categories where it is hard to leverage prior return experiences, customers perceive returns as their failures, feel hesitant to purchase the next time, and thus are more likely to reduce their future purchases. When customers can leverage the knowledge they acquire from their return experiences, perceived risk is reduced, and they purchase more in their next order. Future research is needed to uncover other potential contingencies that could also explain why in some instances returns can spillover to benefit the firm and in others, they simply damage the bottom line.

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TABLE 1
Empirical Research on Product Returns

Research	Context	Antecedents of Product Returns	Contingencies of Antecedents' Impacts	Consequences of Product Returns	Contingencies of Product Returns' Impact
Current research	E-tail: traditional online channel vs. mobile channel	Channel utilization: traditional online channels vs. mobile channels; Discount promotions	Channel utilization moderates discount promotions	Future buying behavior	Product categories with various levels of customer learning
Seo, Yoon, and Vangelova (2016)	Survey: Shoe category	Shopping plan: planned vs. unplanned	Buying motivation: hedonic vs. utilitarian motivations		
Bell, Gallino, and Moreno (2015)	E-commerce vs. in-store	Open "showrooming" stores			
Maity and Arnold (2013)	Survey: E-commerce vs. in-store	Search as expense or experience			
Powers and Jack (2013)	In-store retail	Return policies: liberal vs. restricted; customer opportunism; switching barriers	Gender and store brand		
Bower and Maxham (2012)	E-commerce	Return policies: free return vs. fee return	Retailer attribution for returns vs. Self attribution for returns	Post-return spending	
Ofek, Katona, and Sarvary (2011)	E-commerce vs. in-store			Strategies of adding another channel (online or in -store)	Product categories with various levels of need for inspections; price competition intensity
Anderson, Hansen, and Simester (2009)	Catalog retail			Return's value to customers and benefits to firms	Return policies: lenient vs. restricted; product categories with various levels of product fit; customers' channel utilization (online vs. in-store)
Peterson and Kumar (2009)	E-commerce, catalogs, telephone, and outlets	Gifts; holidays; new cross buy; new channel; new sales items		Future buying behavior; future marketing resource allocation	
Bechwati and Siegal (2005)	Experiment: CD players	Presentation of alternatives: sequentially vs. simultaneously	Whether customers are inoculated consumers		
Wood (2001)	Catalog retail	Return policies: lenient vs. restricted	Catalog vs. bricks-and-mortar		

TABLE 2
Study 1: Variable Descriptions

Variables	Notations in Equations	Operationalization in Sample A	Operationalization in Sample B
Return percentage	Return percent	The ratio of number of items returned to total number of items purchased for an order	The ratio of number of items returned to total number of items purchased for an order
Channel utilization	CU	Assign 1 to orders placed on mobile channels and 0 to orders placed on traditional, online channels	Assign 1 to orders placed on mobile channels and 0 to orders placed on traditional online channels
Discount promotion	discount	Ratio of the discount amount to the order's original cost	Ratio of the discount amount to the order's original cost
Order spending	total spending	The total spend of an order	The total spend of an order
Average item price	price	The average item price of an order	The average item price of an order
Order recency	recency	The number of days since last purchase	The number of days since last purchase
Holiday	holiday	Promotion events[a] such as New Year (January 1st - 3rd), Laba Festival (January 27th), Chinese New Year (February 3rd to 21st), Women's Day (March 8th), and Fashion Day (March 25th)	Promotion events[a] such as Christmas (December 24-25), New Year (December 31), Singles Day (November 11th), Double Twelve Day (December 12), and National Day (October 1st to 7th).
Shipping fee	shipping	Free shipping is offered by company A for all orders, thereby being eliminated in the main analyses	Shipping fee that is charged by company B for a given order

a. Researchers consult with the marketing managers of Company A and B about the promotion activities launched during their corresponding study periods.

TABLE 3
Study 1: Summary Statistics and Correlations of All Variables (Sample A)

Variables	Mean	SD	Frequency (Yes=1)	1	2	3	4
Dependent Variable							
1. Product return percentage	1.65%	9.83		1			
Variables of Interest							
Channel utilization (mobile channel)			49.33%				
2. Discount promotion	5.01%	8.74		.044**	1		
Control Variables							
3. Order spending[a]	219.97	176.65		-.024**	.378**	1	
4. Average item price[a]	157.92	94.36		-.151**	.131**	.531**	1
5.Order recency	63.89	79.29		-.019**	-.018**	.040**	.007
Holiday			63.47%				

n=21,030 orders placed by 8,848 customers
**. Correlation is significant at the 0.01 level (two-tailed test).
*. Correlation is significant at the 0.05 level (two-tailed test).
A: Unit: Chinese Yuan. 1 Chinese Yuan = .15 US Dollar

TABLE 4
Study 1: Summary Statistics and Correlations of All Variables (Sample B)

Variables	Mean	SD	Frequency (Yes=1)	1	2	3	4	5
Dependent Variable								
1. Product return percentage	10.99%	31.28		1				
Variables of Interest								
Channel utilization (mobile channel)			50.27%					
2. Discount promotion	38.28%	8.75		-.017**	1			
Control Variables								
3. Order spending[a]	153.95	89.42		.167**	-.009	1		
4. Average item price[a]	32.58	19.17		.050**	-.007	.118**	1	
5.Order recency	71.70	58.40		.068**	.025**	.092**	-.086**	1
6. Shipping fee[a]	2.70	4.61		-.101**	.003	-.394**	-.014**	-.036**
Holiday			15.07%					

n=36,221 orders placed by 14,336 customers

**. Correlation is significant at the 0.01 level (two-tailed test).

*. Correlation is significant at the 0.05 level (two-tailed test).

a: Unit: Chinese Yuan. 1 Chinese Yuan = .15 US Dollar

TABLE 5
Study 1: Main Analyses Results

Variables	Sample A		Sample B	
	B	Std. Err	B	Std. Err
Channel utilization	-.004***	.001	-.007 [a]	.004
Discount promotion	.064*	.028	.170	.119
Channel utilization * Discount promotion	-.043*	.022	-.001***	.000
Order spending	.000***	.000	.001***	.000
Average item price	-.000***	.000	.000***	.000
Order recency	.000[a]	.000	.000***	.000
Holiday	-.000	.001	.010*	.005
Pscore	.001	.010	-.250***	.053
$\text{Copula}_{\text{discount}}$	-.002	.001	-.012	.010
Shipping fee	NA	NA	-.003***	.000

Sample A:n = 21,030; Sample B: n = 36,221; [a]. p<.10; *. p<.05; **. p<.01; ***. p<.001.

TABLE 6
Study 1: Robust Check 2 – Various Forms of Dependent Variables

Variables	Sample A				Sample B			
	Dummy DV Return or Not		Count DV Number of Items Returned		Dummy DV Return or Not		Count DV Number of Items Returned	
	B	Std. Err	B	Std. Err	B	Std. Err	B	Std. Err
Channel utilization	-.495***	.098	-.364***	.086	-.084[a]	.047	-.087*	.036
Discount promotion	5.373**	1.788	6.258***	1.693	2.751	1.82	3.551*	1.751
Channel utilization * Discount promotion	-2.831[a]	1.627	-2.431[a]	1.486	-.010***	.002	-.007*	.003
Order spending	.005***	.000	.005***	.000	.005***	.000	.008***	.000
Average item price	-.026***	.002	-.026***	.001	.006***	.001	-.015***	.001
Order recency	.002**	.001	.002**	.004	.004***	.000	.004***	.000
Holiday	-.014	.103	-.006	.098	.127[a]	.056	.121*	.053
Pscore	-.053	.885	.070	.758	-3.086***	.667	-1.611**	.556
$Copula_{discount}$	-.112	.107	-.152	.100	-.210	.158	-.224	.154
Shipping fee	NA	NA	NA	NA	-.061***	.006	-.051***	.009

TABLE 7
Study 2: Summary Statistics and Correlations of All Variables (Sample A and B)

	Variables	Mean	SD	Frequency (Yes=1)	1	2	3	4
Sample A	**Dependent Variable**							
	1.Ln (purchase amount)	5.19	1.32		1			
	Variables of Interest							
	Return (or not)			50.00%				
	Control Variables							
	2.Discount promotion	.11	.12		.16**	1		
	3.Average item price[a]	154.38	67.54		.29**	.27**	1	
	4.Order recency	7.63	15.77		-.04	-.16**	-.18**	1
	Channel utilization			42.99%				
	Holiday[b]			20.23%				
Sample B	**Dependent Variable**							
	1.Ln (purchase amount)	4.86	.59		1			
	Variables of Interest							
	Return (or not)			50.00%				
	Control Variables							
	2.Discount promotion	.38	.09		.07**	1		
	3.Average item price[a]	54.15	12.52		.53**	.03**	1	
	4.Order recency	34.66	33.22		.20**	.13**	.12**	1
	5.Shipping fee	2.18	4.19		-.42**	.01	-.23**	-.02
	Channel utilization			76.98%				
	Holiday[b]			18.98%				

Sample A: n= 2,224; Sample B: n= 9,006

**. Correlation is significant at the 0.01 level (two-tailed test).
*. Correlation is significant at the 0.05 level (two-tailed test).
a: Unit: Chinese Yuan. 1 Chinese Yuan = .15 US Dollar
b: National holidays

TABLE 8
Study 2: Main Analyses Results (Sample A and B)

Variables	Sample A		Sample B	
	B	Std. Err	B	Std. Err
Return	1.020***	.06	-.057***	.01
Discount promotion	.105	.22	.232***	.05
Average item price	.004***	.00	.020***	.00
Channel utilization	.216***	.05	.002	.01
Order recency	.014***	.00	.002***	.00
Shipping fee	NA	NA	-.043***	.00
Holiday	.144*	.06	-.003	.01
Propensity score	1.227*	.57	.448***	.08
AICC[b]	7,004.28		11,478.83	

Sample A: n=2,224 orders & customers; [a]. p<.10; *. p<.05; **. p<.01; ***. p<.001.
Sample B: n=9,006 orders & customers; [a]. p<.10; *. p<.05; **. p<.01; ***. p<.001.
b: Finite Sample Corrected Akaike's Information Criterion

APPENDIX A1
Study 1: Descriptive Statistics of Propensity Score Model Variables Before and After Matching (Sample A)

	Before Matching					*After Matching*				
Behavioral Characteristics in Pre-Study Period	***Mobile Mean***	***Mobile SD***	***Traditional Mean***	***Traditional SD***	***ND[a]***	***Mobile Mean***	***Mobile SD***	***Traditional Mean***	***Traditional SD***	***ND[a]***
Ln (# of items returned +1)	.06	.21	.08	.25	.08	.01	.07	.01	.10	.04
Ln (% of orders returned +1)	.01	.05	.01	.31	.04	.00	.02	.00	.02	.02
Ln (total item quantity+1)	1.58	.78	1.69	.85	.13	.89	.43	.89	.44	.01
Ln (total spending amount+1)	5.82	.98	5.96	1.02	.14	4.95	.64	4.96	.66	.01
Ln (# of orders purchased +1)	1.24	.58	1.26	0.61	.03	.81	.29	.81	.31	.01
Ln (Total discount % + 1)	.09	.10	.11	.12	.16	.02	.06	.02	.06	.00
Demographics:										
Is from Province										
Beijing	.05	.22	.08	.27	.12	.06	.23	.06	.23	.00
Chongqing	.02	.14	.02	.14	.01	.02	.13	.02	.15	.01
Fujian	.06	.23	.05	.21	.03	.06	.23	.06	.23	.00
Gansu	.01	.09	.01	.09	.00	.00	.07	.00	.07	.01
Guangdong	.13	.34	.16	.37	.09	.17	.38	.18	.38	.00
Guangxi	.02	.14	.02	.14	.00	.01	.12	.01	.12	.00
Guizhou	.01	.12	.01	.12	.00	.01	.11	.01	.10	.02
Hainan	.01	.09	.01	.08	.02	.00	.07	.01	.07	.01
Hebei	.03	.16	.03	.16	.01	.02	.16	.02	.15	.01
Heilongjiang	.02	.13	.02	.12	.01	.02	.12	.02	.12	.00
Henan	.03	.17	.03	.16	.02	.03	.16	.03	.17	.02
Hubei	.04	.20	.03	.18	.04	.04	.19	.04	.19	.00
Hunan	.03	.18	.03	.18	.01	.03	.16	.03	.16	.01
Inner Mongolia	.01	.12	.01	.11	.02	.01	.11	.01	.11	.00
Jiangsu	.09	.28	.07	.25	.08	.09	.29	.09	.29	.00
Jiangxi	.02	.15	.02	.14	.03	.02	.13	.02	.14	.01
Jilin	.01	.11	.01	.11	.00	.01	.10	.01	.09	.01
Liaoning	.03	.17	.03	.17	.01	.03	.17	.03	.16	.01
Ningxia	.00	.06	.00	.06	.00	.00	.05	.00	.05	.00
Qinghai	.00	.04	.00	.04	.01	.00	.03	.00	.03	.02
Shandong	.05	.21	.04	.20	.02	.05	.22	.05	.22	.00
Shanghai	.06	.24	.07	.26	.03	.07	.26	.07	.26	.00
Shannxi	.02	.15	.02	.15	.00	.02	.14	.02	.13	.01
Shanxi	.02	.14	.02	.12	.05[a]	.01	.12	.02	.12	.01
Sichuan	.04	.19	.05	.21	.04	.04	.20	.04	.20	.00
Tianjin	.02	.14	.02	.14	.01	.01	.11	.01	.11	.01
Tibet	.00	.03	.00	.04	.02	.00	.02	.00	.02	.00
Xinjiang	.01	.11	.01	.11	.01	.01	.09	.01	.09	.00
Yunnan	.03	.16	.02	.16	.00	.02	.15	.02	.14	.00
Zhejiang	.09	.29	.08	.27	.05	.10	.30	.10	.30	.01
Is from rural	.17	.38	.20	.40	.06	.12	.32	.12	.32	.00

[a]: Normalized difference in means; Sample A: Before matching-23,165 customers used mobile channels and 42,358 customers used traditional online channels; After matching-4,424 customers used mobile channels and 4,424 customers used traditional online channels.

APPENDIX A1
Study 1: Descriptive Statistics of Propensity Score Model Variables Before and After Matching (Sample B)

	Before Matching					*After Matching*				
Behavioral Characteristics in Pre-Study Period	***Mobile Mean***	***Mobile SD***	***Traditional Mean***	***Traditional SD***	***ND[a]***	***Mobile Mean***	***Mobile SD***	***Traditional Mean***	***Traditional SD***	***ND[a]***
Ln (# of items returned +1)	.07	.22	.08	.24	.06	.07	.23	.07	.23	.01
Ln (% of orders returned +1)	.05	.15	.06	.17	.07	.05	.15	.05	.15	.00
Ln (total item quantity+1)	2.27	.67	2.22	.68	.07	2.27	.67	2.25	.67	.02
Ln (total spending amount+1)	5.22	.79	5.14	.81	.09	5.21	.08	5.19	.78	.02
Ln (# of orders purchased +1)	.94	.31	.93	.31	.02	.94	.31	.94	.31	.02
Ln (Total discount % + 1)	.27	.08	.28	.08	.10	.27	.08	.27	.08	.00
Demographics:										
Is from Province										
Beijing	.05	.21	.06	.23	.05	.05	.22	.05	.22	.00
Chongqing	.02	.13	.02	.13	.01	.02	.14	.02	.14	.01
Fujian	.06	.24	.05	.23	.03	.07	.25	.06	.24	.02
Gansu	.00	.06	.00	.06	.01	.00	.05	.00	.07	.03
Guangdong	.17	.37	.22	.41	.14	.16	.37	.17	.37	.01
Guangxi	.03	.17	.03	.16	.02	.03	.18	.03	.17	.02
Guizhou	.01	.10	.01	.09	.02	.01	.10	.01	.10	.01
Hainan	.01	.09	.01	.10	.01	.01	.11	.01	.09	.02
Hebei	.03	.17	.03	.16	.01	.03	.17	.03	.17	.01
Heilongjiang	.01	.08	.01	.11	.06	.00	.06	.00	.05	.01
Henan	.04	.18	.03	.16	.05	.03	.17	.03	.18	.00
Hubei	.04	.20	.01	.11	.06	.03	.17	.03	.18	.01
Hunan	.03	.18	.03	.16	.04	.03	.17	.03	.17	.01
Inner Mongolia	.00	.06	.01	.08	.04	.00	.05	.00	.06	.01
Jiangsu	.13	.33	.10	.30	.08	.12	.32	.12	.32	.01
Jiangxi	.02	.14	.02	.13	.03	.02	.14	.02	.14	.01
Jilin	.00	.06	.00	.06	.01	.00	.06	.00	.07	.01
Liaoning	.02	.15	.02	.14	.02	.02	.15	.02	.15	.01
Ningxia	.00	.04	.00	.04	.00	.00	.05	.00	.04	.01
Qinghai	.00	.02	.00	.03	.02	.00	.02	.00	.02	.01
Shandong	.04	.20	.05	.21	.03	.04	.20	.05	.21	.01
Shanghai	.07	.25	.08	.27	.05	.07	.26	.07	.26	.00
Shannxi	.02	.14	.02	.13	.03	.02	.15	.02	.14	.01
Shanxi	.01	.11	.01	.09	.04[a]	.01	.09	.01	.09	.01
Sichuan	.04	.20	.04	.19	.02	.04	.21	.05	.21	.01
Tianjin	.02	.14	.02	.13	.00	.02	.13	.02	.14	.01
Tibet	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Xinjiang	.00	.07	.01	.08	.03	.00	.07	.00	.07	.01
Yunnan	.01	.12	.02	.14	.04	.02	.13	.01	.11	.03
Zhejiang	.09	.29	.08	.27	.03	.09	.29	.09	.29	.00
Is from rural	.15	.36	.13	.34	.06	.14	.35	.15	.35	.02

[a]: Normalized difference in means; Sample B: Before matching-40,811 customers used mobile channels and 9,950 customers used traditional online channels; After matching-7,168 customers used mobile channels and 7,168 customers used traditional online channels.

APPENDIX A2
Study 1: Estimates for the Propensity Score Logit Model (Sample A and B)

	Independent Variables	Sample A: Utilized Mobile Channel?		Sample B: Utilized Mobile Channel?	
		Logit b	**Std. Err**	**Logit b**	**Std. Err**
Demographic factors	Is from Province: Beijing	$-.29^{***}$	.04	$-.12^{*}$	.06
	Is from Province: Chongqing	-.06	0.5	$-.15^{*}$	.07
	Is from Province: Fujian	.07	.04	$-.12^{*}$	.05
	Is from Province: Gansu	-.06	.07	$-.28^{*}$	.12
	Is from Province: Guangdong	$-.16^{***}$	.03	$-.27^{***}$	.05
	Is from Province: Guangxi	-.00	.05	-.11	.06
	Is from Province: Guizhou	-.03	.05	-.09	.08
	Is from Province: Hainan	.05	.07	$-.27^{**}$	.08
	Is from Province: Hebei	.02	.04	$-.14^{*}$	.06
	Is from Province: Heilongjiang	-.01	.05	$-.58^{***}$	.08
	Is from Province: Henan	.02	.04	-.03	.06
	Is from Province: Hubei	.09	.04	.02	.06
	Is from Province: Hunan	.01	.04	-.07	.06
	Is from Province: Inner Mongolia	.04	.05	$-.50^{***}$	.10
	Is from Province: Jiangsu	$.13^{***}$	.04	-.01	.05
	Is from Province: Jiangxi	$.10^{*}$	.05	-.05	.06
	Is from Province: Jilin	-.00	.05	-.10	.11
	Is from Province: Liaoning	-.03	.04	-.11	.06
	Is from Province: Ningxia	.00	.09	-.19	.16
	Is from Province: Qinghai	-.16	.13	$-.54^{*}$	.23
	Is from Province: Shandong	.01	.04	$-.24^{***}$	.05
	Is from Province: Shanghai	$-.10^{**}$	.04	-.08	.06
	Is from Province: Shannxi	-.03	.05	-.05	.06
	Is from Province: Shanxi	$.18^{***}$	.05	.05	.08
	Is from Province: Sichuan	$-.11^{**}$	.04	$-.15^{**}$	.05
	Is from Province: Tianjin	-.08	.05	.03	.07
	Is from Province: Tibet	$-.42^{*}$	.16	NA	NA
	Is from Province: Xinjiang	.04	.06	$-.45^{***}$	.10
	Is from Province: Yunnan	-.01	.04	$-.39^{***}$	.07
	Is from Province: Zhejiang	$.08^{*}$	.04	$-.10^{*}$	.05
	Is from rural	$-.13^{***}$	.01	$.24^{***}$	.03
Customers' past experience factors	Ln (# of items returned +1)	$-.28^{***}$	.04	.05	.08
	Ln (% of orders returned +1)	$.74^{***}$	.16	$-.41^{***}$	.11
	Ln (total item quantity+1)	$-.10^{***}$	.02	$.06^{*}$	.02
	Ln (total spending amount+1)	$-.14^{***}$	.01	$.08^{***}$	.02
	Ln (# of orders purchased +1)	$.36^{***}$	.02	$-.14^{***}$	.03
	Ln (Total discount % + 1)	$-.35^{***}$	.07	$-.69^{***}$	.08

*.p<.05; **. p<.01; ***. p<.001; Sample A: Log pseudo-likelihood = -41,852.12; n = 65,523; Sample B: Log pseudo-likelihood = -24,738.45; n = 50,745

APPENDIX A3
Study 2: Descriptive Statistics of Propensity Score Model Variables Before and After Matching (Sample A and B)

	Sample A: Before Matching					**Sample A: After Matching**					**Sample B: Before Matching**					**Sample B: After Matching**				
Behavioral Characteristics in Pre-Study Period	***No Return Mean***	***No Return SD***	***Return Mean***	***Return SD***	***ND[a]***	***No Return Mean***	***No Return SD***	***Return Mean***	***Return SD***	**ND**	***No Return Mean***	***No Return SD***	***Return Mean***	***Return SD***	**ND**	***No Return Mean***	***No Return SD***	***Return Mean***	***Return SD***	**ND**
Ln (total spending amount+1)	5.72	.87	5.85	.89	.14	5.86	.83	5.79	.90	.08	5.19	.81	5.23	.77	.05	5.16	.79	5.16	.74	.01
Ln (Total discount amount+ 1)	2.27	2.16	2.72	2.23	.20	2.69	2.23	2.57	2.22	.05	4.40	.96	4.39	.92	.01	4.36	.96	4.35	.89	.01
Ln (Total shipping amount+ 1)											1.16	1.28	.98	1.21	.14	1.01	1.22	1.04	1.22	.03
Ln (# of orders purchased on mobile +1)	.45	.51	.42	.50	.07	.38	.49	.39	.49	.02	.66	.49	.63	.48	.04	.64	.46	.63	.46	.01
Ln (# of orders purchased during holidays +1)	.62	.46	.65	.45	.05	.64	.46	.64	.44	.00	.05	.17	.05	.17	.00	.04	.17	.04	.17	.00
Ln (# of orders purchased during weekend +1)	.13	.30	.10	.27	.09	.10	.27	.11	.28	.02	.28	.38	.27	.37	.04	.26	.37	.26	.37	.01
Ln (# of orders returned +1)	.04	.17	.07	.24	.14	.07	.23	.07	.23	.04	.06	.20	.20	.35	.47	.05	.18	.05	.18	.01
Ln (# of orders purchased +1)	.46	.58	.42	.55	.07	.43	.57	.42	.55	.01	.40	.49	.38	.48	.04	.35	.46	.35	.46	.02
Order$_j$'s Characteristics																				
Product importance	150.11	70.51	116.72	31.69	.61	119.84	37.81	118.28	32.59	.04	52.20	12.32	56.39	10.83	.36	54.85	11.03	54.88	11.12	.00
Channel utilization	.55	.50	.26	.44	.62	.26	.44	.29	.45	.07	.75	.43	.74	.44	.02	.75	.43	.74	.44	.01
Discount promotion	.07	.11	.09	.04	.18	.08	.13	.09	.04	.11	.38	.09	.37	.08	.08	.38	.08	.37	.08	.22
Shipping											2.95	4.75	1.37	3.53	.38	1.83	3.89	1.78	3.89	.01
Order size	1.70	1.14	1.23	.55	.52	1.30	.67	1.25	.58	.07	6.06	3.41	6.97	3.53	.26	6.56	3.38	6.52	3.20	.01
Order recency	70.18	34.05	79.04	36.84	.25	79.07	35.83	77.49	36.66	.04	118.85	55.57	135.61	55.86	.30	127.14	54.48	127.44	52.32	.01
Holidays	.26	.44	.18	.39	.18	.18	.39	.19	.39	.03	.06	.24	.10	.30	.15	.08	.27	.07	.26	.03
Demographics																				
Mobile phone penetration (province level)	110.51	30.93	113.80	32.10	.10	114.18	33.65	113.13	31.51	.03	111.64	30.65	110.71	30.09	.03	111.13	30.45	110.87	30.25	.01
Is from middle sized city											.65	.48	.67	.47	.04	.66	.47	.66	.47	.01
Is from rural	.13	.34	.12	.33	.03	.12	.32	.12	.33	.02	.14	.35	.14	.35	.01	.15	.36	.14	.35	.03

[a]: Normalized difference in means; Sample A: Before matching-1,241customers returned their first orders and 50,721 customers did not return their first orders; After matching-1,112 customers returned their first orders and 1,112 customers did not return their first orders; Sample B: Before matching-7,363 customers returned their first orders and 51,449 customers did not return their first orders; After matching- 4,503 customers returned their first orders and 4,503 customers did not return their first orders.

APPENDIX A4

Study 2: Estimates for the Propensity Score Logit Model (Sample A and B)

	Sample A: Returned the Order?		Sample B: Returned the Order?	
Pre-Study Period Behavioral Characteristics	**Logit b**	**Std. Err**	**Logit b**	**Std. Err**
Ln (total spending amount+1)	.251***	.02	-.041*	.02
Ln (Total discount amount+ 1)	.022**	.01	-.080***	.01
Ln (Total shipping amount+ 1)			.003	.01
Ln (# of orders purchased on mobile +1)	.312***	.03	-.003	.02
Ln (# of orders purchased during holidays +1)	.082*	.04	.064	.04
Ln (# of orders purchased during weekend +1)	-.028	.05	-.037a	.02
Ln (# of orders returned +1)	.527***	.07	1.117***	.03
Ln (# of orders purchased +1)	-.492***	.04	-.042	.03
Order$_j$'s Characteristics				
Product importance	-.005***	.00	.008***	.00
Channel utilization	-.732***	.03	-.031	.02
Discount promotion	.020***	.12	.003***	.00
Shipping			-.029***	.00
Order size	-.365***	.02	-.008**	.00
Order recency	.003***	.00	.002***	.00
Holidays	-.169***	.03	.094***	.03
Demographics				
Mobile phone penetration (province level)	.002***	.000	-.000	.00
Is from middle sized city			.072**	.02
Is from rural	.022	.04	.082**	.03

[a]. p<.10; [*]. p<.05; [**]. p<.01; [***]. p<.001.
Sample A: n= 51,962; Model fit: Log likelihood = -4,980.07
Sample B: n= 58,812; Model fit: Log likelihood = -20,153.56

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