ENHANCING E-COMMERCE PERFORMANCE: PRODUCT RETURN AND ONLINE CUSTOMER REVIEW PERSPECTIVES

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ABSTRACT

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E-commerce has grown to become one of the most commonly used shopping channels by customers and firms, especially in the retail sector. However, e-commerce faces critical challenges, such as high product return rates and struggles to optimize the effectiveness of marketing mix. My dissertation uses two essays to tackle the above two challenges in an effort to enhance the performance of e-commerce. Essay 1, via two studies, examines the antecedents and consequences of product returns in e-commerce from the perspectives of channel coordination (coordinating mobile channels and traditional online channels) and customer learning. Study 1, analyzing two large-scale transaction-level datasets from two companies in different categories indicates that the use of the mobile channel can lessen e-commerce return rates, especially for highly promoted products, but increase the return rates of high-priced products, compared to traditional online channel use. Study 2 finds that for product categories requiring much (little) learning from customers, return experiences reduce (enhance) customers' future purchases. As a result, this essay offers actionable channel coordination strategies to firms by analyzing why people return their online purchases and what roles the channels play in driving returns. In this process, we offer answers to questions such as what products ought to be presented on what channels, to manage returns more efficiently. More importantly, this essay also brings attention to managers that they need to understand the nature of returns objectively; namely, returns can be good or bad and that they are better off in applying the corresponding strategies to cope with their returns. Essay 2 aims to enhance marketing efforts' effectiveness by leveraging online

customer reviews (OCRs) in e-commerce. Drawing on anchor and adjustment theory, and using two studies via differing research methods, we propose that the relationships between OCRs and marketing efforts are dynamic and non-linear, which helps capture the complexity of consumers' decision making. Study 1 develops an information-varying effect model to depict the dynamic and non-linear relationships between OCR volume and a company's 4Ps marketing efforts in influencing product sales. Study 2 uncovers why the impacts of companies' marketing efforts vary over levels of OCRs using a lab experiment. Briefly, the findings show that the impact of a price discount is positive, with a diminishing trend as OCR volume increases, to the extent that at medium and high volumes of OCR, discounts no longer impact customer confidence, which ultimately drives purchase intentions. In conclusion, essay 2 provides the most holistic insight into how a wide range of marketing tactics can impact sales in the presence of customer reviews. These results demonstrate not only significant contingencies on the effectiveness of marketing efforts on consumer spending but a comprehension of why the influences of marketing efforts are reduced as OCR availability increases. Neither of these aspects have been captured in prior research on OCRs. The consequence is that managers should not develop strategies based on static models but should dynamically update marketing allocations as more OCR information becomes available.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

KEY TO ABBREVIATIONS

OCR = Online Customer Review

IVEM = Information Varying Effect Model

INTRODUCTION TO DISSERTATION

E-commerce has enhanced firms' profit streams and changed consumers' shopping experiences substantially. According to Statista, e-commerce revenue amounted to $409,208 million in the United States in 2017, with an expected annual growth rate of 8.4% over the next five years. The worldwide retail e-commerce market was almost $1.69 trillion in 2017, with expectations of topping $2.5 trillion by 2022. In the U.S., there were 191 million online shoppers in 2016, a figure expected to increase to 247 million by 2022, basically engaging almost every adult in the country at that time. Consequently, researchers have been keen to investigate the unique features of e-commerce and online channels that set them apart from offline channels (e.g., Chu, Chintagunta, and Cebollada 2008; Gensler, Neslin, and Verhoef 2017; Shankar, Smith, and Rangaswamy 2003).

However, despite the benefits e-commerce offers to customers and its strategic importance for every firm's long-term development, e-commerce itself faces daily challenges that compromise firms' profits. One of these is that e-commerce suffers higher return rates than brick-and-mortar stores (the return rate is 30 percent for e-retailers and 8.89 percent for brick-and-mortar stores) (Saleh 2016). These higher return rates stem from the fact that online channels display a seemingly infinite number of substitute products (low search costs) (Hung 2012; Lynch and Ariely 2000; Reichheld and Schefter 2000) and do not give customers the opportunity to touch and feel a product before purchasing it (lack of fit) (KengKau, Tangm, and Ghose 2003). However, scant research exists on how to manage returns (Petersen and Kumar 2015) and managers are eager to obtain guidance on how to cope with their returns more efficiently. Additionally, the extant literature overwhelmingly expresses the negative economic costs of returns to companies; however, recent studies by Petersen and Kumar (2009; 2010; 2015) articulate that a reasonable number of product returns may maximize firm profits over the long run. These seemingly conflicting arguments in the literature call for a thorough comprehension of returns' impacts on consumers' future purchases: are returns good or bad? The answer to this question is important, because without fully understanding the nature of returns, managers cannot design and implement effective strategies to manage returns and extract maximum profits. As a result, essay one of my dissertation is dedicated to tackling product return issues in the scope of e-commerce.

Specifically, I aim to answer two questions: 1) What factors influence return decisions and, particularly, what roles do channels play? 2) Are returns good or bad? In other words, essay one intends to study the antecedents and consequences of returns in e-commerce. First, I intend to analyze why people return their online purchases, and propose that the discrepancies between the perceived product formed in the purchasing process and the actual product realized after receiving it eventually trigger returns by activating cognitive dissonance. Information search is proposed to be the remedy to decrease the discrepancies discussed above. Then, I draw on the multichannel literature, which suggests that various modes of purchase (channels) offer different features to customers and further alter customers' shopping experiences and outcome behavior (Ansari, Mela, and Neslin 2008; Mallapragada, Chandukala, and Liu 2016; Neslin et al. 2006; Verhoef, Kannan, and Inman 2015). I conjecture that since mobile channels and traditional online channels provide different information search experiences to customers, channels may play a significant but strategically unleveraged role in driving returns. Also, marketing information is displayed to customers via channels. For the same information, different ways of presenting it may affect the decoding processes customers use to understand information and that information's influence on their decisions and behavior (Mallapragada, Chandukala, and Liu

2016). In summary, this research theorizes and examines the dual roles of channels in driving returns: 1) the direct role in driving returns, and 2) the moderating role in altering marketing information's impacts on returns. Consequently, this research's pre-eminent intended contribution is to justify the roles of channels in driving returns and provide firms with channel coordination strategies, such as what products ought to be presented on what channel, to manage returns more efficiently.

Second, to answer the second question of essay one on whether returns are good or bad, I first deem return experiences to be a learning process for customers to learn products and brands, a process that facilitates their future purchase decisions(Anderson and Simester 2013; Petersen and Kumar 2015). However, some products are more difficult to learn than others (Anderson and Simester 2013). Thus, essay two posits that given various levels of customer learning difficulty across product categories, returns can be both good and bad. Consequently, this research's paramount intended contribution is to understand returns' after-effects more thoroughly by taking customer learning into account and to offer a more precise way of evaluating the nature of returns to managers.

Another challenge e-commerce faces is how to make better use of marketing efforts. Marketing tactics are used every day in e-commerce to entice customers to purchase; however, in the meantime, customers attach tremendous weight to online customer reviews (OCRs) when making purchasing decisions (eMarketer 2017). It seems logical for managers to consider marketing tactic plans while incorporating OCRs' impacts on customers' decisions. Yet, the extant literature fails to provide either a complete or a consistent understanding of the relationships between OCRs and marketing efforts (i.e., Chong et al. 2016; Lu et al. 2013), despite the fact that prior research has consistently demonstrated that OCRs have strong direct effects on sales. As a result, managers who likely understand the intuitive appeal of more online reviews are still left wondering how many reviews are enough and whether resources should be more focused on generating OCRs or traditional marketing efforts. Without an answer to this question, managers cannot have confidence in the effectiveness of their commonly used marketing efforts. With this being said, essay two of my dissertation aims to render a more accurate demonstration on the true relationships between OCRs and firm-initiated marketing efforts and capture the complexity of online decision making.

Drawing on anchoring and adjustment theory, which suggests customers' perceptions based on previous information can be updated as new information varies (Dagger and Danaher 2014; Hibbert, Winklhofer, and Temerak 2012), I propose that the relationships between OCRs and marketing efforts are dynamic and non-linear. It is necessary to account for the relative impact of marketing efforts as OCR availability grows from absence to full proliferation. In addition, the narrow array of marketing efforts (discount and advertising) assessed in the OCR literature is unable to provide sufficient guidance for managers' daily business planning. As a result, essay two's objective is to depict the true relationships (i.e., dynamic and non-linear) between OCRs and a more inclusive suite of marketing actions, including the entire marketing mix—Price (discount), Promotion (free shipping), Product (product variety), and Place (multichannel offering)—in influencing customers' purchase decisions. The critical intended contribution of this essay is not only to provide the most holistic insights into how a wide range of marketing tactics can impact sales in the presence of customer reviews, but also to suggest that the management of online marketing efforts and the role OCRs play in the decision-making process are far more dynamic than prior research leveraging static data suggests. It is wise that marketers properly update marketing allocations dynamically as more OCR information becomes available in an effort to extract more profits.

The rest of this dissertation begins by presenting essay one and essay two separately and sequentially. Then, I close with a brief summary of the theoretical and managerial contributions of the dissertation.

ESSAY ONE

Strategically Improving Product Returns in Multichannel E-Commerce

Abstract

Product returns in e-commerce carry substantial costs and challenges that need to be untangled in a quest to offer improved strategic remedies that can be used in reverse marketing channels. In this context, we collect large-scale transaction-level data from two companies which have been ranked number one in their respective sub-categories of the apparel industry by Alibaba (in annual sales), and then conduct two studies (Study 1: n=510,453 + 157,908 customers; Study 2: n=51,962 + 58,812 customers). Using prospect theory and rational choice theory, we find that appropriately leveraging channel coordination (mobile and traditional online channels) can be a strategic remedy to reduce returns in e-commerce. Specifically, mobile channels are associated with lower return rates due to the larger consideration set customers establish via them, which is especially true for highly promoted products. Meanwhile, high-priced products are less likely to be returned in traditional online channels. The consequences of returns depend on product categories and for product categories that require much (little) learning from customers, return experiences reduce (enhance) customers' future purchases.

Keywords: Product Returns, E-commerce, Channel Coordination, Mobile Channel, Customer Learning

Introduction

The retail industry has changed drastically over the last two decades, initially with the arrival of computer-interface shopping and, more recently, with the emerging of mobile channels and social media platforms (Verhoef, Kannan, and Inman 2015). One of the most significant concerns in the retail industry today is product returns, due to their staggering cost (The Retail Equation 2015). For example, in the United States alone, retail returns amount to about $300 billion annually (only 23 countries have greater GDP than $300 billion). Another $100 billion is allocated to the infrastructure of reverse logistics systems that companies need to have in place for the product returns (Petersen and Kumar 2015).

E-commerce has grown to be one of the most commonly used shopping channels by customers and firms, especially in the retail sector. Unique to e-retailers, they are more challenged by product returns than brick-and-mortar stores because product returns in the e-retailer setting are much higher (the return rate is 30 percent for e-retailers and 8.89 percent for brick-and-mortar stores) (Saleh 2016). As such, our research scope is to better understand returns in the e-commerce setting. Broadly, the high return rate in e-commerce stems from the fact that online channels display a seemingly infinite number of substitute products (low search costs) (Hung 2012; Lynch and Ariely 2000; Reichheld and Schefter 2000) and provide no ability for customers to touch and feel a product before purchasing it (lack of fit) (KengKau, Tangm, and Ghose 2003). These online characteristics amplify the discrepancies between what customers want, what they think they bought online, and what they actually receive. Consequently, the discrepancies between the perceived product and the real product trigger product returns that have strategic implications for firms' bottom-line performance.

Unfortunately, the extant literature offers only limited remedies to decrease the cost of product returns, especially e-commerce. Bell, Gallino, and Moreno (2015) suggest that having show-and-tell opportunities (i.e., offline showrooms) can complement online channels, leading 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 that can be realized for the customer base compromise the effectiveness of this strategy. Anderson, Hansen, and Simester (2009) and Bower and Maxham (2012) state that if the product returns are at the customers' expense, a customer is less likely to return products. Despite this truth, implementing such a negatively oriented, almost punishment-focused strategy, has been shown to adversely affect customers' future purchase intentions (Bower and Maxham 2012). As such, beyond the suggestions of offline showrooms and customers being stuck with the return expenses, managers are eager to obtain guidance to better manage e-commerce return rates.

Positively, despite the negative economic costs of returns, 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. These seemingly conflicting arguments in the literature call for the development of a thorough understanding of product returns' impact on consumers' future purchases: basically, are product returns good or bad? Almost naïve as a question, it is rather important to address this question because without fully understanding the nature of returns, managers are unable to design and implement effective strategies to manage product returns.

Consequently, to bridge the gap in the literature, we address what we know and what we need to know about product returns in e-commerce (e.g., antecedents and consequences). Specifically, we analyze the roles of marketing channels (mobile channels and traditional online channels[1]) in driving product returns in e-commerce and how customer learning alters the consequences of returns. Drawing inferences from prospect theory and rational choice theory, we note that purchase decisions and return decisions are separate but interrelated. Rationally, when customers are faced with unbearable discrepancies between the perceived product formed in the purchasing process and the actual product realized after receiving the product, cognitive dissonance is activated and a product return is often the solution (Powers and Jack 2013). At a basic level, companies that enhance information search in the purchasing process and offer channel platforms that allow for such search can improve risk reduction and product understanding, and eventually reduce the discrepancies. Information search is an effective learning mechanism for customers, and companies need to know how to better facilitate and implement such a marketing channel strategy across multi-channels to create a compelling competitive differentiation in e-commerce.

To seek strategic levers that assist customers in better searching for product information, we draw on the multichannel literature. This literature suggests that various modes of purchases (channels) offer different features to customers which lead to different shopping experiences and behaviors (Ansari, Mela, and Neslin 2008; Mallapragada, Chandukala, and Liu 2016; Neslin et al. 2006; Verhoef, Kannan, and Inman 2015). As a starting point, using our data, Table 1-1[2] demonstrates the preliminary manifest differences between the two focal channels and the distinct customer behaviors while using these channels (i.e., mobile and traditional online channels). Given the differences between mobile and traditional online channels, we posit that customers may conduct more information search on mobile channels, but receive more thorough

[1] 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. These traditional online channels mostly need a Wi-Fi environment to connect to the Internet. This classification is based on the levels of the devices' portability.

[2] This information was obtained from Company A. We collaborated extensively with Company A during this investigation.

and detailed information on traditional online channels. As a preliminary, channel utilizations can be a significant, yet strategically unleveraged, driver of lowering product returns. In addition, for the same marketing information (i.e., discount and product), diverse ways of presenting the information on various channels may affect the decoding processes that customers use to understand the information and the information's influences on customers' decisions and behavior (Mallapragada, Chandukala, and Liu 2016). Building on these preliminaries, we theorize and examine the dual roles of channels in driving returns: 1) the direct role in driving returns, and 2) the moderating role in altering marketing information's impacts on returns. Subsequently, we provide firms with options for channel coordination strategies, such as what products ought to be presented on what channel to manage returns more efficiently.

Additionally, we answer the practical question of whether returns are good or bad. Return experiences are an invaluable learning experience that customers can employ to get to know brands and products better (Anderson and Simester 2013; Petersen and Kumar 2015). However, for customers, some products are more difficult to learn about than others (Anderson and Simester 2013). Thus, we suggest that taking into account the variations in customer learning difficulty across product categories may assist researchers and practitioners in contextualizing the impact of returns on customers' future purchases. In doing so, we offer a more precise way of evaluating the consequences of returns for firms on a case-by-case basis.

Theories and Hypotheses

Petersen and Kumar (2009) suggest that the firm-customer exchange process comprises three key elements: firm-initiated marketing communications, customer buying behavior, and customer product return behavior. The marketing literature has stressed the first two elements in numerous studies (e.g., Elsner, Krafft, and Huchzermeier 2004; Mohan, Sivakumaran, and

Sharma 2013; Venkatesan and Kumar 2004). However, product returns have not received the same depth and breadth of attention (cf. Petersen and Kumar 2009). This is unfortunate since product returns are not only a hassle for a firm's marketing channels, they are also a drain on overall firm profitability (Bernon et al. 2016; Petersen and Kumar 2009). Additionally, given that customer acquisition is expensive and time consuming (Villanueva, Yoo, and Hanssens 2008; Walker 2001), customer retention is extremely valuable (Gustafsson, Johnson, and Roos 2005). The bottom line is that product returns and ineffective reverse logistics add obstacles to customer retention and future customer acquisition (Petersen and Kumar 2010). At the same time, Petersen and Kumar (2009) have provided evidence for the competing theorizing that product returns are not necessarily bad and, instead, can sometimes lead to increased future purchases by customers.

Unfortunately, much of the research to date has overly stressed the forms of return policies and their differentiated influences on product returns (cf. Petersen and Kumar 2015). Unsurprisingly, the results indicate 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, Hansen, and Simester 2009; Bower and Maxham 2012). But, this strategy adversely affects the customer's future purchase intention and the long-term profitability and perhaps even viability of a company (cf. Bower and Maxham 2012; Petersen and Kumar 2015). In general, imposing any constraints on customers' choices or behaviors is not an advisable strategy for firms that aim for stable customer relationships and long-term profits.

With this premise, we aim to answer two core questions: 1) What factors influence return decisions and particularly, what roles do channels play? 2) Are product returns bad or not? Figure 1-1 summarizes the core relationships studied. Now, before answering the questions, our starting point has to be why people often return online purchases. According to Lawton (2008), low product quality, broken packages, and damaged products are not the primary return reasons for the contemporary retail sector. Instead, buyer remorse and cognitive dissonance, which are psychological reasons, are much more prominent (Lawton 2008; Powers and Jack 2013; 2015). Accordingly, we underscore and build on how these psychological harms take place.

We draw on prospect theory, noting that people make decisions (i.e., purchase a product) by analyzing the potential gain (i.e., benefit of product) and the perceived loss, or sacrifice (i.e., cost of product), based on the information that is available (Kahneman and Tversky 1979; Sweeney, Soutar, and Johnson 1999). When customers deem that the perceived benefit exceeds the perceived cost, they make the purchase, according to their prospect. However, when customers receive the products, another theory seems to become more applicable: rational choice theory (Coleman and Fararo 1992). If customers discover that the realized cost exceeds the realized benefit, cognitive dissonance will occur, which needs to be resolved by undoing the original and regretted behavior (Harmon-Jones and Harmon-Jones 2007). In our context, the undone behavior is the product returns which take place due to customers' rationality and the associated rational choice. Customers compare the cumulative cost and the realized benefit, which is based on conclusive evidence, but not a prospect, thus resulting in a rational choice that could be product returns. Hence, purchase and return decisions are separate but interrelated.

We can safely summarize that it is the *discrepancies between perceived benefit and realized benefit as well as between perceived cost and realized cost* (for parsimony, we refer to the italic phrase as the discrepancies, hereafter), that result in cognitive dissonance, which further leads to product returns. Namely, once a customer places an order, he/she may recognize that the benefit of the product has been overestimated and/or the cost has been underestimated. For instance, he/she might realize the extent to which he/she needs the product has been inflated through commercials and promotions. The customer may also discover that they could have bought this product for a lower price in another store or that the product is simply different from what he/she thought while purchasing it. When these discrepancies occur, the customer's reaction may be to return the purchased product.

The remedy that aids customers in reducing their return propensities is enhanced product information search, which occurs while utilizing the marketing channels as a part of the shopping experience, as product related information is displayed via shopping channels to potential customers. E-commerce contains two primary sub-channels: mobile channels and traditional online channels. We assert that the various features of these channels can adjust the prospect of the product formed by potential customers (e.g., Ansari, Mela, and Neslin 2008; Verhoef, Neslin, and Vroomen 2007). This further adjusts the discrepancies and return propensities. In addition, the information presented on different channels may be decoded in different ways and influence customer decisions/behaviors (i.e., product returns) differently across channels (Ansari, Mela, and Neslin 2008; Mallapragada, Chandukala, and Liu 2016). In this research, we consider two types of marketing information: promotions (i.e., discount promotion) and products (i.e., product importance: economic value of the category or the financial risk of the category). These two types of marketing information are commonly presented by firms to entice purchases.

The e-commerce literature suggests that the two sub-channels of online shopping (i.e., computer-interface channels and mobile channels) have differential information benefits for customers (Aksoy et al. 2013; Wang, Malthouse, and Krishnamurthi 2015). A core difference between the channels is the type and amount of information search available and used. On the one hand, mobile channels empower customers more than computer-interface channels/

traditional online channels by giving them the ability to access, on the spot, information from multiple sources, compare product prices, and obtain relevant promotion information in a timely manner (Joy, Sherry, Venkatesh, and Deschenes 2009; Kim, Wang, and Malthouse 2015; Wang, Malthouse, and Krishnamurthi 2015). Simply put, mobile shopping is more than just accessing web pages on a mobile device. Aksoy 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. We draw on the literature and suggest that the uniqueness of mobile channels is that they offer convenience and high accessibility of information (Aksoy et al. 2013; Balasubramanian, Peterson, and Jarvenpaa 2002; Lai, Debbama, and Ulhas 2012; Wang, Malthouse, and Krishnamurthi 2015). These two features are made possible by the mobile phone's portability (Lai, Debbama, and Ulhas 2012). As a result of their unique features, as compared to traditional online channels, mobile channels can motivate adopters to purchase more in the future (Kim, Wang, and Malthouse 2015) and increase their order rate and order size (Wang, Malthouse, and Krishnamurthi 2015).

On the other hand, traditional online channels can provide deep and comprehensive information to channel users, due to the larger screen sizes, higher resolutions, and richer interactive environments, as compared to mobile channels (Sweeney and Crestani 2006). Users can easily input information on traditional keyboards, as compared to using mobile channels and smartphone devices (Shankar et al. 2010). Additionally, due to the limitations of mobile devices' sizes and functionality (Wang, Malthouse, and Krishnamurthi 2015), firms had to adjust their strategies and display more detailed information regarding a product on their traditional online channels. Customers can also easily open multiple products on traditional online channels and compare and contrast them side-by-side to make their purchasing decisions (Baeza-Yates and Ribeiro-Neto 1999; Sweeney and Crestani 2006).

In essence, the merits of traditional online channels are the potential drawbacks of mobile channels, and vice versa. Traditional online channels are unable to offer accessibility of information anytime, when customers may be in need, since a laptop or a tablet is not as portable as a mobile phone. However, traditional online channels can offer more detailed information about a product. Hence, firms may utilize these two channels in a coordinated strategic readiness-manner to provide better shopping experiences to customers (e.g., displaying suitable marketing information across channels) according to the channels' unique features and customers' specific needs. In this research, we go beyond the structural differences between the channels, and focus on their differences regarding the amount of information searched and the types of information obtained by customers to offer a unique, implementable strategic remedy for the very high product returns in e-commerce

Direct Effects of Channels on Product Returns

Drawing on the multichannel literature, we propose that various contexts (i.e., modes of purchases) may lead customers to behaving distinctively. Specifically, we argue that people conduct more information searches on mobile channels than on traditional online channels. To theoretically support this contention, we draw inferences from the consideration set literature. The consideration set is defined by Robert and Lattin (1991) as the brands or products that a consumer would consider buying in the near future. Robert and Lattin (1991) articulate that information search is associated with the consideration set. The greater the information search, the larger the consideration set (Sambandam and Lord 1995). As noted earlier, the primary features of mobile channels are high accessibility of information and convenience as compared to traditional online channels. As such, we assert that people establish a larger consideration set and conduct more information search while browsing on mobile channels as compared to traditional online channels.[3]

Furthermore, as more information searches are accomplished and especially more alternatives are viewed on mobile channels, customers become more 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. Using mobile channels, customers can easily revisit their shopping cart to remove any unwanted products and/or add any desirable products. Thus, mobile channels help customers become more informed regarding what product is right for their needs, which consequently fosters a relatively accurate prospect of the purchased product and reduces the discrepancies.

That said, the depth of information retrieved on mobile channels is potentially compromised as compared to traditional online channels due to the mobile phone's screen size and operational maneuvers of scrolling, etc. (Shankar et al. 2010; Sweeney and Crestani 2006). Traditional online channels can provide more interactive environments for customers to contrast products and receive more detailed information about a certain product (Baeza-Yates and Ribeiro-Neto 1999). However, to define the scope and limit alternative explanations data noise, we study the clothing industry (women's and children's apparel), which may mitigate the impact of this specific drawback of mobile channels. In general, product pictures, brief descriptions, and

[3] 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. Table 1-1 indicates that the average number of products browsed on the mobile channel is significantly larger than that on the traditional online channel (Mmobile = 5.90, Mtraditional online = 2.25, t-value = 83.89, $p < .00$). 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's mobile commerce report in United States.

number of options on mobile channels are likely to be adequate for customers to judge a clothing product. Hence, we expect that:

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

H_2: Mobile channel utilization's negative impact on product returns, as compared to traditional online channel utilization, is mediated by the consideration set.

Moderating Roles of Channels on Impacts of Marketing Information

Other than the main effects of channel utilization on product returns, we theorize that channel utilization moderates the effects of marketing information in e-commerce. This moderating role derives from the fact that firms display their marketing information, such as promotion and product features, to customers via various channels, and drastic differences between channels may alter the impact of marketing 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. Again, the two sub-channels of e-commerce (traditional, mobile) offer drastically different information search experiences to customers. Theoretically, it is logical to hypothesize the moderating role of these channel environments in influencing the impacts of marketing information.

We consider two types of information that are drivers of returns whose impacts may be altered by channels: discount promotion and product importance. Discount promotions are useful cues for customers that aid in cognitive evaluations of products and purchase decisions (Raghubir 2004). For long, we have known that overwhelming promotional events have the possibility of inflating impulsive shopping behavior (KengKau, Tang, and Ghose 2003). Such impulsive shopping adheres to little rational and consequential thinking (Beunza and Stark 2012), which yields 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.

In this environment, mobile channels bring convenience and high accessibility of information to customers, enabling them to compare more brands and/or products whenever needed. This eventually leads customers to make (more) informed decisions on what purchases provide the most value to them. In other words, when customers contrast alternatives during a purchase, they likely end up weighing information about the product other than simply the discount. As viewing enough alternatives and reconsidering options are keys to quell the impulsive sentiments that affect customer behavior, mobile channel utilization may lead customers to more rational and accurate decisions. Thus, we hypothesize that:

H_3: Channel utilizations moderate 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 than traditional online channels.

A great importance of a purchase, or the high economic cost of a purchase, is associated with intensive information seeking before making the purchase. This phenomenon is prominent in online contexts because customers perceive higher risks when purchasing expensive products online (D'Alessandro, Girardi, and Tiangsoongnern 2012). Based on information theory, intensive information search can offset the perceived and actual risk and uncertainty of purchases (Borst and Theunissen 1999; Klir and Wierman 1999). With our data collected from apparel companies, it is reasonable to assume that purchasing a product in an expensive product category (fur coat, suit) involves more thorough information searches, as compared to purchasing a product in a less costly category (t-shirt). The thorough information searching process adds more accuracy in building a product prospect before purchase and further leads to fewer discrepancies and then less remorse and cognitive dissonance when customers receive the product.

However, given the important categories' high value and risk, customers may require relatively deep information in addition to viewing more alternatives. This requirement amplifies the return propensity of expensive products that are placed on mobile devices because mobile channels are unable to offer thorough information and easy comparisons for customers to judge the products. The illustrations of products in expensive categories on mobile channels may enlarge the discrepancies between reality and the prospect. In opposite, the deep and thorough information and the ability to contrast multiple products simultaneously offered by traditional online channels aid customers in evaluating expensive products more efficiently and accurately, leading to fewer returns. Thus:

> H_4: Channel utilizations moderate the relationship between product importance and product returns, such that the relationship is weakened (i.e., less negative) when purchases are made on mobile channels than traditional online channels.

Consequences of Product Returns

The product return literature overwhelmingly focuses on costs of product returns (i.e., Anderson, Hansen, and Simester 2009; Bower and Maxham 2012). However, in a series of product return papers, Petersen and Kumar (2009, 2010, 2015) also articulate benefits of having a reasonable amount of product returns lead to maximization of firm profits over time. The premise is that return behaviors can lower customers' perceived risk of current and future purchases. Given the conflicting arguments in the literature, part of our research involves uncovering a more complete picture of product returns' consequences: are returns good or bad?

Product return experiences essentially become part of the process that customers engage in to learn about products and brands (Anderson and Simester 2013; Petersen and Kumar 2009). According to contingency theory, the value of a resource depends on the context within which it is deployed (Lawrence and Lorsch 1967). Thus, we assert that the impact of product returns on customers' future purchases are contingent on product categories. This is because some product categories demand more customer learning than others. Children's apparel, for example, requires more customer learning than women's apparel because of the frequent changes in children's sizes (Anderson and Simester 2013). Children's clothing are also often bought as presents, by others, which likewise increases complexity in learning and adds additional obstacles to successful purchases. In these cases that product categories are difficult to learn, past return experiences with these categories barely provide useful inferences but amplify the perceived risk of future purchases because these experiences add less learning value, if at all, yet add more anxiety and caution to customers' future purchase decisions. Thus, customers may reduce the purchasing amount to offset risk and anxiety. On the other hand, when product categories are easier to learn for customers (i.e., women's apparel vs. children's clothing), product returns help reduce perceived risk of future purchases because of the knowledge learned from prior returns, oftentimes leading to more purchases.

H_5: Customer 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: Drivers of Product Returns

Data and Variables

To examine drivers of product returns with the focus on channel coordination, we collaborated with two companies which have been ranked number one in their respective sub-categories of the apparel industry by Alibaba in terms of annual sales. Both companies are online-selling only companies. As such, they have 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 (The Retail Equation 2015), making the industry context very relevant for our focus on product return research. Also, obtaining datasets from different sub-categories of the apparel industry and two vastly different companies add generalizability to the findings. To attain comparable results, all variables are operationalized in consistent fashion across samples (see operationalization details in Table 1-2).

One variable of interest is labelled as the mobile channel, a proxy for channel utilization that is represented by a binary variable, assigning 1 if an order was placed on the mobile channel and 0 if an order was placed on the traditional online channel. We assume that if a customer processed the payment of an order on the mobile channel or the traditional online channel, he or she browsed and shopped for the product(s) primarily on the same channel. This is plausible since both companies A and B only operate online. Thus, the potential information sources for their customers to get to know the products are the mobile and traditional online channels. And situations such as trying on products in the offline channel and then purchasing them online, or vice versa, would be effectively eliminated. However, due to the trust issue of processing payment on mobile channels, one may conjecture that consumers use mobile channels to browse and add items to baskets and then use traditional online channels to process the payment. If this argument is true, the conversion rate (i.e., ratio of number of customers to number of visitors) of mobile channels would be lower than that of traditional online channels. Table 1-1 shows that the conversion rate of the mobile channel in company A is significantly higher ($M_{mobile} = .008$, $M_{traditional\ online} = .005$, t-value = 7.06, $p < .00$) than that of the traditional online channel. The same result is revealed in the Criteo's (2016) U.S. State of Mobile Commerce report. Thus, our assumption is valid. The discount variable is operationalized as the ratio of the discount amount to the order's original cost. The product importance variable is the average original price of all items of a certain product category (i.e., sweater and pants). Given that the unit of analysis is a customer order, we decided that the most expensive product category of an order to be the product importance of that order.

We also include several covariates to address potential confounding effects. Rural area and region[4] where the customers reside are included because people from different areas may vary in income levels and culture, leading to various return rates. In addition, since both companies send their products to customers from their dedicated warehouses located at their headquarters, controlling for regions and rural areas can also eliminate the confounding effect of delivery time which has been shown to be positively related to anticipated regret and return propensity (Anderson and Zahaf 2009; Lim and Dubinsky 2004). For instance, based on geographic distance and transportation infrastructure, customers from west and north China and/or rural areas receive products with longer delivery times than those from other areas of

[4] We only controlled these two variables in Sample A's analysis because we utilized PSM to match these variables in Sample B prior to the main analysis. Thus, it is needless to control these two variables in the main analysis of Sample B.

China. We also control for customers' past experiences with the brand[5], number of items purchased in an order, and order recency. Company A offers free shipping on all purchases, while company B sometimes charges shipping fees based on customers' locations. Thus, the analysis of Sample B includes shipping fee as an additional covariate.

Empirical Challenge: Endogenous Selection Bias of Channel Utilization

As indicated, we use a dummy variable (named mobile channel in the data) to be the proxy of channel utilization. However, the primary challenge of this operationalization is self-selection bias that can potentially distort the parameter estimates. Explicitly, whether customers opt to use mobile channels or traditional online channels to make a certain purchase is subject to self-selections. Without removing this bias, results of the relationship between channel utilizations and returns may stem from customers' heterogeneity rather than different channel features. To enhance rigor and ability to infer causality, we apply two methods to eliminate confounding effects of self-selection (one in each sample).

Sample A's self-selection control-approach is control function methodology (Petrin and Train 2010). We use the relevant instrumental variables (IVs) approach. The IVs that we include in the control function approach are the order placement time related factors demonstrated in Einav, Levin, Popov, and Sundaresan (2014). Einav et al. (2014) show that people are more likely to use mobile channels during weekend, midnight, and commute times (7am to 9am and 5pm to 7pm). This assertion is especially applicable in China where the majority of people take public transportations to work, and they have access to mobile channels only while they are on the road. However, there is no logical link between shopping time and product return propensity. We also include holidays and province (where customers are from) as additional IVs. Hence, we

[5] We only controlled this variable in Sample A's analysis because we utilized PSM to match this variable in Sample B prior to the main analysis. Thus, it is needless to control this variable in the main analysis of Sample B.

determine that the five IVs (whether the order is placed during commute time, midnight, weekend, or holidays, and province dummy variables) can control the potential selection bias on channel utilization.

Additionally, using Sample B, we employ propensity score matching (PSM) to account for the endogenous selection bias of channel utilization. We use the pre-study period data (January – June 2015) to create a matched sample with customers who have the same possibility of using mobile channels for their first order in the post-study period (July – December 2015). In reality, they happened to use different channels for their orders. In doing so, we are one step closer to demonstrate the casual effects of channel on product returns, demonstrate the reliability of the findings in Sample A, and add a layer of support.

Sample A: Analyses and Results

As indicated earlier, we employ a control function approach using two-stage estimation (i.e., Petrin and Train 2010) to model the potential bias of channel utilization. We include five IVs in the first-stage analyses, as discussed. Then, we estimate the correction term in the first stage by regressing the endogenous variable (i.e., mobile channel) on the five instrumental variables using the pooled probit model, shown in Equation 1:

$$\ln\left(\frac{P\_MC_{ij}}{1-P\_MC_{ij}}\right) = z_{ij}^{MC}\lambda^{MC} + \eta_{ij}^{MC} \quad (1)$$

where P_MC_{ij} indicates the probability that customer *i* used the mobile channel to place order *j*, MC is the abbreviation of mobile channels, λ^{MC} is the unknown parameter vector, z_{ij}^{MC} is the vector of exogenous variables, and the random errors η_{ij}^{MC}. Additionally, because the endogenous variable is a dummy variable, to obtain accurate residuals that can be used in the second stage, we transform $\widehat{\eta_{ij}^{MC}}$ calculated from Equation 1 to generalized residuals $\widehat{\delta_{ij}^{MC}}$ and insert $\widehat{\delta_{ij}^{MC}}$ in the full model (shown in Equation 2). Results of the first stage are shown in Table 1-3. Table 1-4 contains summary statistics and correlations of all variables used in main analyses.

After that, we conduct tests using a random effect model with clustered robust standard errors. The logit regression is employed due to the use of a binary dependent variable (i.e., whether an order is returned or not). To prepare the panel data, we limited the sample to customers who placed at least two orders during the study period (October 2014 to March 2015), resulting in an analyzed dataset that contains 1,338,510 orders placed by 510,453 customers. The full model is shown in Equation 2.

$$\ln\left(\frac{P_{return_{ij}}}{1-P_{return_{ij}}}\right) = \beta_0 + \beta_1 discount_{ij} + \beta_2 importance_{ij} + \beta_3 MC_{ij}$$

$$+\beta_4 MC_{ij} * discount_{ij} + \beta_5 MC_{ij} * importance_{ij} + \beta_6 experience_{ij} + \beta_7 quantity_{ij} +$$

$$\beta_8 recency_{ij} + \beta_9 region_i + \beta_{10} rural_i + \gamma_1 \widehat{\delta_{ij}^{MC}} + \varepsilon_{ij} \qquad (2)$$

where P_return$_{ij}$ is the probability that customer *i* returned order *j*, $discount_{ij}$ and $importance_{ij}$ are discount promotion and product importance, respectively, MC_{ij} is a binary variable that indicates whether customer *i* used a mobile channel to place order *j* (see details of these variables in Table 1-2), and the random errors ε_{ij}.

As we were only able to obtain the consideration set information for the time from October 2014 to December 2014, the data for this time period was utilized for the mediation test. The dataset contains 500,509 orders placed by 213,440 customers. The same set of covariates is included and the control function approach is used to correct for the selection bias of the mobile channel variable. To test the mediating role of the consideration set, we conduct a meditation test using bias-corrected bootstrapping (10,000 replications) (Preacher and Hayes 2004) with a dichotomous outcome variable (i.e., return or not).

The results shown in Table 1-5 demonstrate that the mobile channel has a direct and negative impact on product return propensity ($b = -.222$, $p < .01$). 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 mobile channel and discount ($b = -.008$, $p < .001$) suggests that channel utilizations weaken (i.e., less positive) the relationship between discount and product returns. A one standard deviation increase in discount increases the return propensity of a mobile order to a less extent than a traditional online order. Thus, H_3 is supported. The statistical significance of the interaction coefficient between the mobile channel and product importance ($b = .002$, $p < .001$) suggests that channel utilizations weaken (i.e., less negative) the relationship between product importance and product returns. A one standard deviation increase in product importance decreases a mobile order's return propensity to a less extent than a traditional online order. Thus, H_4 is also supported.

The mediation results show that the indirect effect of the mobile channel on product returns through the consideration set is negative and significant (IE = -.079, bias-corrected 95% CI = -.083, -.074), supporting H_2. More so, once the consideration set is added in the equation, the direct effect of the mobile channel becomes insignificant ($b = -.130$, $p > .10$). These results add significant support to our contention that mobile channels lessen return rates as compared to traditional online channels due to the extra information search done on mobile channels.

Sample B: Analyses and Results

Using Sample B, we implement PSM to create a matched sample in an effort to address possible self-section issues using the pre-study period data (January – June 2015; i.e., Iacus, King, and Porro 2011; Wang, Malthouse, and Krishnamurthi 2015). We select a control group of customers who used traditional online channels to purchase their first orders during the post-study period (July – December 2015) and have characteristics (shown in Table 1-6) similar to the treatment group of customers. The customers in the treatment group used mobile channels to purchase their first orders in the post-study period. Following Wang, Malthouse, and Krishnamurthi (2015), we also assert that these characteristics (customers' prior shopping behaviors and demographic characteristics) are determinants of the likelihood of people using mobile or traditional online channels. The assumption is that two customers with similar propensity scores (difference <.0000005) have a similar likelihood of being assigned to the treatment group. In reality, one used a mobile channel (i.e., in the treatment group) and the other used a traditional online channel (i.e., in the control group). Consequently, it is more plausible to claim that their differential return propensities are caused by different channel features as all else is kept constant. We follow the steps used in Wang, Malthouse, and Krishnamurthi (2015).

The original dataset to create the matched sample contains 157,908 customers, 75.51 percent of whom used mobile channels to purchase their first orders in the post-study period. We limit our sample to customers who placed at least one order during the pre-study period and one order during the post-study period. First, using logistic regression, we model the relationship between covariates – customers' shopping behavior during the pre-study period and demographic characteristics – and whether a customer used a mobile channel for the first order in the post-study period. The probability that customer *i* uses a mobile channel for the first order is shown in Equation 3:

$$P_i = \Pr(MC_i = 1 | \ln(\boldsymbol{v_i} + 1),\ \boldsymbol{d_i}) \qquad (3)$$

where MC_i is a binary variable that indicates whether customer *i* used a mobile channel to purchase his first order in H2 2015, vector $\boldsymbol{v_i}$ contains customers' past shopping behavior-related covariates, and vector $\boldsymbol{d_i}$ contains demographic covariates (see all covariates in Table 1-6). The logistic regression (shown in Equation 4) assigns the propensity score $\widehat{P_i}$ to each customer:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \boldsymbol{d_i}\lambda_1' + \ln(\boldsymbol{v_i}+1)\,\lambda_2' + \varepsilon_i \qquad (4)$$

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.

Results of the logistic regression are presented in Table 1-6. The pseudo R-square is .375, exceeding the satisfaction hurdle (Wang, Malthouse, and Krishnamurthi 2015). We utilize 1:1 matching and the nearest-neighbor matching algorithm to create the matched sample, which contains 7,162 customers in the treatment group and the same number in the control group. 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 Table 1-6. We find that after matching nearly all NDs are reduced, which indicates an improvement in balance. Table 1-7 contains summary statistics and correlations of variables in the matched sample.

The matched sample is used to examine the impacts of channel utilizations on product returns. Per the work by Wang, Malthouse, and Krishnamurthi (2015), we also include the propensity score for each individual in the analyses. We employ logit regression with robust standard errors, shown in Equation 5. See variables' definitions in Table 1-2.

$$\ln\left(\frac{P\_return_i}{1-P\_return_i}\right) = \beta_0 + \beta_1 discount_i + \beta_2 importance_i + \beta_3 MC_i + \beta_4 MC_i * discount_i + \beta_5 MC_i * importance_i + \beta_6 quantity_i + \beta_7 recency_i + \beta_8 holiday_i + \beta_9 shipping_i + \gamma_1 \widehat{P_i} + \varepsilon_i \qquad (5)$$

The results shown in Table 1-8 reveal that the mobile channel has a direct and negative impact on product returns (b = -.207, p < .001), 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. Although the interaction coefficient between the mobile channel and discount ($b = -.005$, $p > .10$) is not significant, the sign of the estimate is consistent with our expectation. We surmise the insignificance derives from Sample B's limited variance in the discount variable and relatively small sample size, as compared to Sample A. Thus, H_3 is not supported. The results also demonstrate the statistical significance of the interaction coefficient between the mobile channel and product importance ($b = .008$, $p < .05$), indicating that channel utilizations positively moderate the relationship between product importance and product returns. That is, as compared to less expensive products, more expensive products purchased on mobile channels are more likely to be returned than those purchased on traditional online channels. Thus, we find support for H_4. Overall, Sample A and B deliver consistent results for the tested hypotheses. However, interestingly, one unexpected finding beyond the hypotheses is that the main effects of discount and product importance reveal opposite signs between Sample A and Sample B. These inconsistencies are likely the consequence of product category differences in Sample A and Sample B.

Study 2: Consequences of Product Returns

To test product returns' impacts on consumers' future purchases, we need to remove the endogenous selection bias of returns, construct return experience as a random treatment, and examine its causal impact on future purchases. To do so, we employ the same PSM method as in Study 1 for Samples A and B[6] to form the matched samples (one from Sample A and the other one from Sample B). The only difference between customers in a matched sample is whether

[6] 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.

they have returned the order$_j$ (the first order they purchased during the post-study period).Using these matched samples, we test the impact of product returns 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 in the post-study period. As we have demonstrated the process of conducting PSM in Study 1, we omit some detailed equations and explanations for parsimony for Study 2.

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 logistic regression, we model the relationship between covariates – customers' shopping behavior during the pre-study period, characteristics of order$_j$ based on our findings in Study 1 on what drives returns, and demographic characteristics (see details in Table 1-9) – and whether a customer returned order$_j$ for Sample A and Sample B. These characteristics are determinants of the likelihood of people returning a certain order according to the return literature and Study 1. Using the same matching algorithm as in Study 1, we analyze the matched samples (2,224 for Sample A; 9,006 for Sample B) with satisfying improvements in balance. Comparisons of NDs before and after matching, results of the logistic regressions, and summary statistics and correlations of variables in the matched samples are shown in Table 1-9 to 1-11. To test H_5, we employ two generalized linear models to examine the impacts of product returns on customers' future purchases across produce categories with various levels of learning difficulty. We also control the propensity score and the characteristics of order$_{j+1}$ in the final model.

The results shown in Table 1-12 indicate that return experiences significantly increase customers' future purchases ($b = 1.020$, $p < .001$) in Sample A, i.e., the low learning difficulty category. However, return experiences significantly decrease customers' future purchases (b = -

.057, $p < .001$) in Sample B, i.e., the high learning difficulty category. Overall, we find support for H_5. Of important note is that we did not include order size in this model because order size and purchase amount are very similar. When employing order size instead of purchase amount, we received corresponding findings to those in Table 1-12.

Discussion

Our research aims to understand mobile and traditional online channels' roles in driving returns and how customer learning adjusts impacts of returns on consumers' future purchases. We primarily focus on the differences in information search between the two channels that lead to various return propensities. However, mobile phones, given their portability, in some situations offer customers opportunities to see a product being used by users before they even think about purchasing this product. This ability to see the product before purchasing is not likely to occur when customers use traditional online channels. Moreover, distinct features of the channels studied may generate various customer behaviors in addition to return behaviors. Also, since the scope of our research was to contrast two sub-channels of e-commerce, we did not include offline channels (e.g., brick-and-mortar stores). It is also plausible that drivers of returns may place differential influences across product categories (see Study 1). Within these limitations and study parameters, our research on strategically improving product returns in multichannel e-commerce offers important theoretical and managerial contributions.

Theoretical Contributions

Our research contributes to the product return, e-commerce, and multichannel literatures in several ways. First, as strategically important as product returns are to firms, especially their e-commerce units, scant research has been conducted to shed light on the remedies to manage return rates (e.g., Petersen and Kumar 2009). The limited insights in this regard are not efficient nor confront the fundamental cause of return instances. Also, much of the extant product return research has generalized across both traditional and mobile online channels. However, we articulate that discrepancies between the perceived product and the actual product trigger cognitive dissonance and consequently returns. Information searches are a good remedy to efficiently reduce the above discrepancies. We show theoretically and empirically that traditional and mobile online channels are different in terms of providing customer information search experiences (i.e., gathering information and reviewing alternatives, Aksoy et al. 2013; Joy et al. 2009; Wang, Malthouse, and Krishnamurthi 2015), thus leading to various return rates and also adjusting marketing information's impacts on return rates.

To advance the product return literature in e-commerce, given the dual roles of the marketing channels (outbound and inbound), we show that channel coordination in online contexts is a remedy for managers to reduce return rates in e-commerce. Specifically, mobile channel usage can reduce return rates and especially help reduce returns of highly promoted products due to the larger consideration set built on mobile channels. Yet, traditional online channels are particularly efficient to reduce the return rates of expensive/important products. Our proposed strategies are manageable and economically efficient for firms, and they also offer what customers need in the purchasing process to avoid returns. Additionally, when the multichannel literature overwhelmingly stresses channel coordination between online and offline channels (i.e., Gensler, Neslin, and Verhoef 2017) and the mobile marketing literature itself has grown to be an individual stream, our research brings inventiveness by shedding light on how to leverage the differences and synergies between sub-channels of e-commerce. As prevalent and dominating as e-commerce is nowadays in the retail sector, it is clearly important to differentiate the uniqueness of online channels as well as understand differences between sub-channels.

Second, dominant claims on costs of returns and recent arguments on positive impacts of returns on future purchases call for research pertaining to comprehensively evaluating the consequences of returns. Our research responds to these needs and articulates that returns can be both good and bad depending on categories of products that are returned by customers. In actuality, return experiences represent one type of learning that customers employ to study brands and products in order to make a more accurate 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. We also introduce the first contingent variable to understanding product return's consequences and reconcile the conflicting arguments in the return literature regarding its aftereffects.

Managerial Contributions

How can channel coordination strategies be optimized in e-commerce? As an example, a retailer in India shut down its entire traditional online channel and shifted all business to the mobile channel. The retailer's managers realized the differences between the two channels and believe the mobile channel alone ought to benefit the business more than the traditional online channel or a combination of the two. That example aside (and as a disclaimer), our suggestion is not that retailers are better off scrapping traditional online channels, at least not without strategically evaluating the costs (loss of sales) versus benefits (fewer product returns). Instead, our intention was to bring to the attention of firms that mobile channels and traditional online channels function differently in terms of providing customer information search experiences.

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 general, our findings lend credence to the argument that mobile channel adoption can reduce product return rates due to the channel's unique features (high accessibility of information and convenience). As such, we suggest that firms should entice those customers with high return rates to use mobile channels to reduce their return rates, such as launching exclusive mobile promotion events and/or sending mobile notifications to those customers. Our results also suggest that for heavily promoted products, firms may consider displaying them on mobile channels exclusively to decrease return rates. Also, because customers require more comprehensive and deeper information when purchasing expensive products, it is wise for firms to consider displaying relatively inexpensive product categories on mobile channels and expensive product categories on traditional online channels. In doing so, firms can partially avoid the mobile channels' limitations, such as small screens and limited functionality.

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, in reality many customers still prefer to use the traditional online channel due to its unique features. Additionally, many companies' e-commerce businesses rely heavily on traditional online channels. 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 set mobile channels apart from traditional online channels. In other words, traditional online channels must help customers conduct larger consideration sets while shopping. Although firms cannot make laptops or tablets more portable, they can facilitate the searching process to help build a larger consideration set. 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 attempts are efforts to encourage customers to conduct more information search, to establish larger consideration sets, and to reduce the discrepancies between the perceived product and the actual one. As a result, customers are less likely to return products purchased. Firms are wise to adjust the design of their traditional online channels by, for example, facilitating the searching process for customers.

Are returns good or bad? Although when customers return products, various costs are generated for firms, we suggest that some return instances can bring entirely different outcomes to firms in terms of customers’ future purchases. 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. 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 use their return experiences in future shopping.

APPENDICES

APPENDIX A: TABLES

Table 1-1 Summary Statistics of Difference between Mobile Channels and Traditional Online Channels (Sample A)[a]

Source		N	Mean	Std. Deviation	T-test for Equality of Means
# products viewed	Mobile	361	2,891,317.11	3,909,252.87	2.31^{*}
	Traditional Online	365	2,333,231.82	2,423,601.55	
# visitors	Mobile	361	483,088.12	498,752.95	-11.10^{***}
	Traditional Online	365	1,039,270.04	815,904.69	
$ amount[a] processed	Mobile	361	4,111,314.11	42,344,390.64	.70
	Traditional Online	365	2,533,068.71	7,543,438.82	
# customers	Mobile	361	4,529.30	20,963.31	-.54
	Traditional Online	365	5,348.73	19,762.96	
Total items sold	Mobile	361	7,306.72	37,450.45	-.56
	Traditional Online	365	8,811.13	34,819.03	
# orders	Mobile	361	7,271.33	37,219.18	-.56
	Traditional Online	365	8,760.39	34,583.44	
$ amount[a] completed	Mobile	361	905,763.34	5,656,690.99	-.38
	Traditional Online	365	1,055,337.86	4,992,057.60	
$ spending[a] per order	Mobile	361	181.77	37.11	-6.29^{***}
	Traditional Online	365	200.04	41.01	
Conversion rate	Mobile	361	.008	.007	7.06^{***}
	Traditional Online	365	.005	.005	
Consideration set	Mobile	361	5.90	.76	83.89^{***}
	Traditional Online	365	2.25	.33	

a: Daily information for year 2014.
b: Unit: Chinese Yuan. 1 Chinese Yuan = .15 US Dollar

Table 1-2 Study 1: Variable Descriptions

Variables	Notations in Equations	Operationalization in Sample A	Operationalization in Sample B
Return		Dummy variable: whether an order was returned or not	Dummy variable: whether an order was returned or not
Mobile channel	MC	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
Product importance	importance	Category price (i.e., average original price of all items in a category)	Category price (i.e., average original price of all items in a category)
Rural	rural	Assign 1 to customers from rural areas and 0 to customers from urban areas	Using PSM, customers' locations are matched prior to the main analyses, thereby being eliminated in the analyses
Region	region	Four regions of China: East, West, North, and South. East is the reference group.	Using PSM, customers' locations are matched prior to the main analyses, thereby being eliminated in the analyses
Order recency	recency	The number of days since last purchase	The number of days since last purchase
Order size	quantity	The number of items purchased in an order	The number of items purchased in an order
Customers' prior experiences	experience	The number of orders purchased since January 2014 until the focal order being studied, regardless of devices used.	Using PSM, prior experiences of customers are matched prior to the main analyses, thereby being eliminated in the analyses
Holiday[a]	holiday	Instrument variable used in the control function approach, thereby being eliminated in the main analyses.	Whether it is a holiday when a given order is purchased. Assign 1 to holidays and 0 to non-holidays. The holidays include such as Singles' day, Double 12 day, New Year, Chinese New Year, National Day, Christmas, and Semiannual sales day.
Shipping	shipping	Free shipping is offered by company A for all orders, thereby being eliminated in the analyses	Shipping fee that is charged by company B for a given order

a: Researchers consult with the marketing manager of the company about the promotion activities launched during the study period.

Table 1-3 Study 1: First-Stage Results of the Control Function Approach (Sample A)

Independent Variables	Logit b	Std. Err
Constant	-.006	.01
Midnight	.238***	.00
Commute time	.080***	.00
Weekend	.052***	.00
Holiday	-.099***	.00
Is from Province: Beijing	-.298***	.01
Is from Province: Chongqing	-.116***	.01
Is from Province: Fujian	-.065***	.01
Is from Province: Gansu	-.066**	.02
Is from Province: Guangdong	-.256***	.01
Is from Province: Guangxi	-.127***	.01
Is from Province: Guizhou	-.026	.02
Is from Province: Hainan	-.123***	.02
Is from Province: Hebei	-.016	.01
Is from Province: Heilongjiang	-.021	.02
Is from Province: Henan	.017	.01
Is from Province: Hubei	.016	.01
Is from Province: Hunan	-.045***	.01
Is from Province: Inner Mongolia	-.075***	.02
Is from Province: Jiangsu	.058***	.01
Is from Province: Jiangxi	.040**	.01
Is from Province: Jilin	-.059**	.02
Is from Province: Liaoning	-.067***	.01
Is from Province: Ningxia	-.072***	.03
Is from Province: Qinghai	-.068	.04
Is from Province: Shandong	-.049***	.01
Is from Province: Shanghai	-.159***	.01
Is from Province: Shannxi	-.042**	.01
Is from Province: Shanxi	.055***	.01
Is from Province: Sichuan	-.119***	.01
Is from Province: Tianjin	-.075***	.02
Is from Province: Tibet	-.120*	.05
Is from Province: Xinjiang	-116***	.02
Is from Province: Yunnan	-106***	.01
Is from Province: Zhejiang	-.016	.01

*.p<.05; **. p<.01; ***. p<.001; Log pseudolikelihood = -918,353; n = 1,338,501

Table 1-4 Study 1: Summary Statistics and Correlations of All Variables (Sample A)

Variables	Mean	SD	Frequency (Yes=1)	1	2	3	4
Dependent Variable							
Product returns (Dummy)			6.42%				
Variables of Interest							
Mobile channel (Dummy)			48.16%				
1. Discount promotion	.06	.10		1			
2. Product importance[a]	161.28	81.24		.21**	1		
Control Variables							
3.Customers' prior experiences	2.55	7.12		.06**	-.00*	1	
4.Order size	1.58	1.10		.42**	.14**	.04	1
5.Order recency	14.89	30.06		.01**	-.11**	.05**	.06**
Rural			13.21%				
Region			East: 40.11%; West: 8.09%; North: 23.63%; South: 28.17%				

n=1,338,501

**. 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 1-5 Study 1: Main Analyses Results (Sample A)

Variables	Main Analyses	
	Logit b	Std. Err
Mobile channel (dummy)	-.222**	.08
Discount Promotion	.058***	.00
Product importance	-.004***	.00
Mobile channel (dummy) * Discount Promotion	-.008***	.00
Mobile channel (dummy)* Product importance	.002***	.00
Rural	-.037**	.01
West	-.172***	.02
North	-.064***	.01
South	-.044***	.01
Customers' prior experiences	.002	.00
Order recency	-.054***	.00
Order size	-.768***	.01
Endogeneity correction residual (Mobile channel)	-.413***	.05
Log Pseudolikelihood	-284,286.23	

n=1,338,501 order and 510,453 customers; [a]. p<.10; *. p<.05; **. p<.01; ***. p<.001.

Table 1-6 Study 1: Descriptive Statistics of Propensity Score Model Variables Before and After Matching and Estimates for the Propensity Score Logistic Model (Sample B)

	Before Matching					After Matching					Is using mobile channel? (Logit Regression)	
Behavioral Characteristics in Pre-Study Period	***TC[a] Mean***	***TC SD***	***MC[b] Mean***	**MC SD**	**ND[c]**	**TC Mean**	**TC SD**	**MC Mean**	**MC SD**	**ND**	**Logit b**	**Std. Err**
Ln (total spending amount+1)	5.01	.83	5.04	.83	.04	4.85	.80	4.81	.78	.05	.019[d]	.01
Ln (Total discount amount+ 1)	4.26	.99	4.24	1.00	.02	4.07	1.01	4.05	.96	.02	-.013[*]	.01
Ln (Total shipping amount+ 1)	1.20	1.27	1.12	1.24	.07	1.02	1.19	1.03	1.19	.01	-.029[***]	.00
Ln (# of orders purchased on mobile +1)	.15	.32	.76	.39	1.70	.48	.42	.47	.41	.02	2.390[***]	.01
Ln (# of orders purchased during holidays +1)	.04	.17	.04	.16	.02	.03	.15	.03	.13	.04	-.039	.03
Ln (# of orders purchased during weekend +1)	.23	.35	.26	.37	.10	.22	.34	.21	.33	.01	-.009	.01
Ln (# of orders returned +1)	.07	.22	.06	.21	.04	.05	.18	.04	.17	.04	-.093[***]	.02
Ln (# of orders purchased +1)	.30	.44	.31	.45	.02	.15	.33	.13	.30	.06	-1.319[***]	.03
Demographics												
Mobile phone penetration (province level)	113.73	31.43	109.65	30.24	.13	109.42	28.32	109.03	27.61	.01	-.001[***]	.00
Is from middle sized city	.63	.48	.66	.47	.06	.69	.46	.71	.46	.03	.038[**]	.01
Is from rural	.13	.34	.16	.37	.07	.13	.34	.13	.33	.01	.079[***]	.02

a: traditional online channels; b: mobile channels;
c: normalized difference in means; Before matching: 119,236 mobile channel users and 38,672 traditional online channel users; after matching: 7,162mobile channel users and 7,162 traditional online
channel users. The equation to calculate ND is $ND_j = \frac{|\overline{x_{jM}} + \overline{x_{jT}}|}{\sqrt{(s_{jM}^2 + s_{jT}^2)/2}}$ and $\overline{x_{jM}}$ and s_{jM}^2 are the mean and variance of the covariate j for the treatment group customers, respectively, and $\overline{x_{jT}}$ and s_{jT}^2 are those for the control group customers.
[d]. p<.10; [*]. p<.05; [**]. p<.01; [***]. p<.001. Model fit: Log likelihood = -54,935.70;
Pseudo Nagelkerke R- square= .375.

Table 1-7 Study 1: Summary Statistics and Correlations of All Variables (Sample B)

Variables	Mean	SD	Frequency (Yes=1)	1	2	3	4
Dependent Variable							
Product returns (Dummy)			9.95%				
Variables of Interest							
Mobile channel (Dummy)			50.00%				
1.Discount promotion	.38	.09		1			
2.Product importance[a]	52.81	12.44		.02*	1		
Control Variables							
3.Order size	5.66	3.41		.07**	.27**	1	
4.Order recency	148.02	63.31		.05**	.14**	-.08**	1
5.Shipping	3.11	4.84		.02	-.30**	-.38**	-.06**
Holidays			12.58%				

n=14,324

**. 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 1-8 Study 1: Main Analyses Results (Sample B)

Variables	Main Analyses	
	Logit b	Std. Err
Mobile channel (dummy)	-.207***	.03
Discount promotion	-.009**	.00
Product importance	.018***	.00
Mobile channel (dummy) * Discount promotion	-.005	.01
Mobile channel (dummy) * Product importance	.008*	.00
Order recency	.000	.00
Order size	.045***	.01
Shipping	-.064***	.01
Holidays	.002	.10
Propensity score	.123	.12
Log Pseudolikelihood	-4,479.23	

n=14,324 orders & customers; [a]. p<.10; *. p<.05; **. p<.01; ***. p<.001.

Table 1-9 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
Mobile channel	.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.

Table 1-10 Study 2: Estimates for the Propensity Score Logistic 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	-.037[a]	.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
Mobile channel	-.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; Pseudo Nagelkerke R-square= .150.
Sample B: n= 58,812; Model fit: Log likelihood = -20,153.56; Pseudo Nagelkerke R-square= .091.

Table 1-11 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			50.00%				
	Control Variables							
	2.Discount promotion	.11	.12		.16**	1		
	3.Product importance[a]	154.38	67.54		.29**	.27**	1	
	4.Order recency	7.63	15.77		-.04	-.16**	-.18**	1
	Mobile channel			42.99%				
	Holidays			20.23%				
Sample B	**Dependent Variable**							
	1.Ln (purchase amount)	4.86	.59		1			
	Variables of Interest							
	Return			50.00%				
	Control Variables							
	2.Discount promotion	.38	.09		.07**	1		
	3.Product importance[a]	54.15	12.52		.53**	.03**	1	
	4.Order recency	34.66	33.22		.20**	.13**	.12**	1
	5.Shipping	2.18	4.19		-.42**	.01	-.23**	-.02
	Mobile channel			76.98%				
	Holidays			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

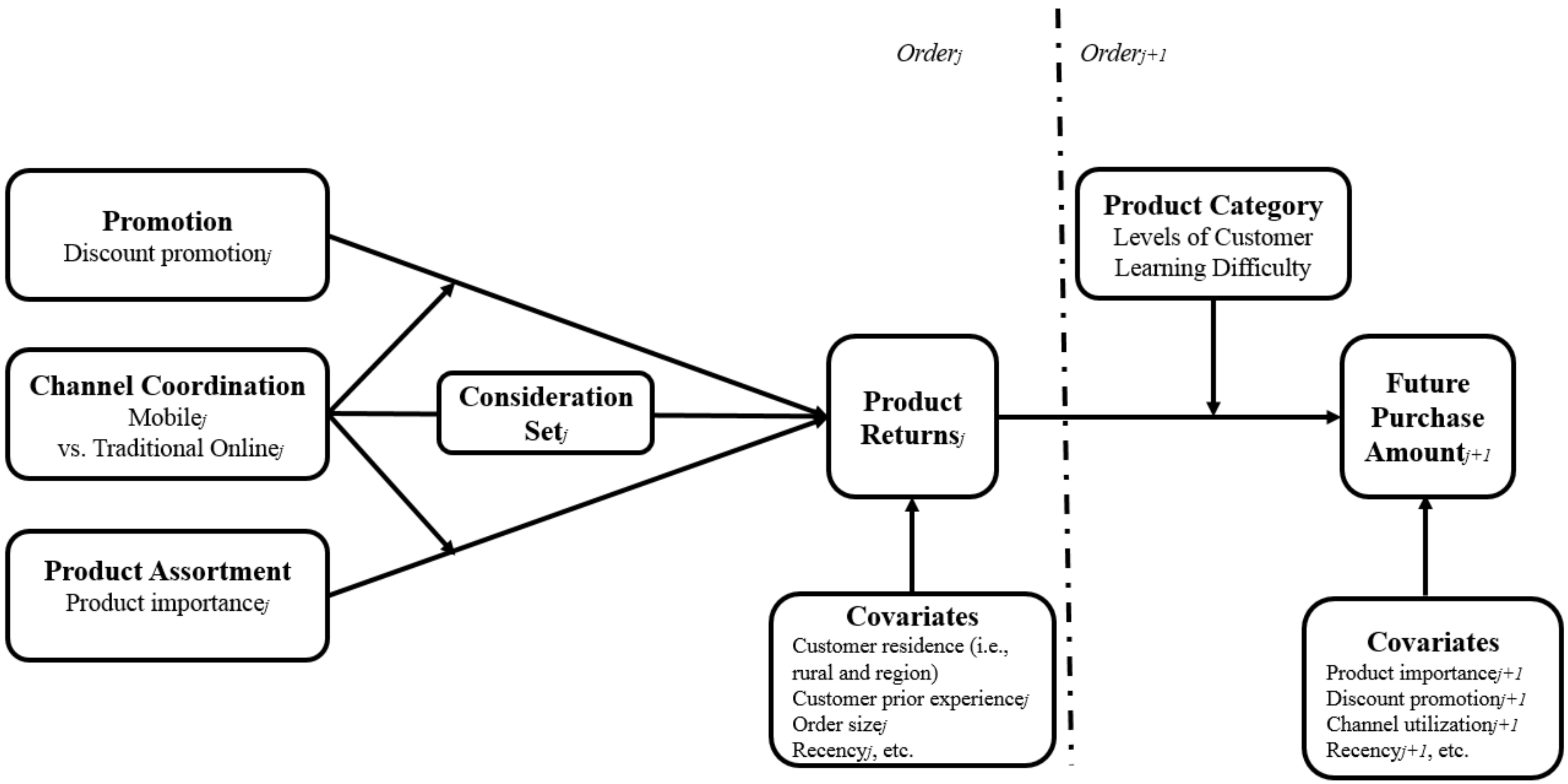
Table 1-12 Study 2: Main Analyses Results (Sample A and B)

Variables	Sample A		Sample B	
	B	Std. Err	B	Std. Err
Return	1.020***	.06	-.057***	.01
Discount promotion	.105	.22	.232***	.05
Product importance	.004***	.00	.020***	.00
Mobile channel	.216***	.05	.002	.01
Order recency	.014***	.00	.002***	.00
Shipping			-.043***	.00
Holidays	.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 B: FIGURES

Figure 1-1 Conceptual Model



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ESSAY TWO

Dynamic Interplays between Online Customer Reviews and Firms' Marketing Efforts

Abstract

Consumers' online decision making has evolved considerably, and dynamic interplays between online customer reviews (OCRs) and companies' marketing efforts have become important knowledge tools for customers. However, research that focuses on impacts of OCRs independent of marketing efforts or examines the static influences of OCRs and a limited set of marketing efforts does not capture the complexity of customers' decision making. Without modeling these dynamic interplays, managers cannot have confidence in the effectiveness of marketing efforts. To close this knowledge gap, we draw on anchoring and adjustment theory in two studies, via differing research methods, to elevate our understanding of OCRs and companies' marketing efforts. Study 1 develops an information-varying effect model to depict the dynamic and non-linear relationships between OCR volume and a company's 4Ps marketing efforts in influencing product sales. Study 2 uncovers why the impacts of companies' marketing efforts' vary over levels of OCRs using a lab experiment. Briefly, the findings show that the impact of a price discount is positive with a diminishing trend as OCR volume increases to the extent that at medium and high volumes of OCR, discounts no longer impact customer confidence, which ultimately drives purchase intentions.

***Keywords**:* Online Customer Reviews, Marketing Efforts, Dynamic Interplays, Information-varying Effect Model, E-commerce

Introduction

Customers' online purchases have evolved significantly over the past decade. For example, some 4-in-5 customers now leverage online customer reviews (OCRs) prior to making purchasing decisions (eMarketer 2017). These customers, on average, also place more trust in OCRs than information provided by friends and family and the brand itself (Salesforce 2016). Unsurprisingly, the emergence of online reviews has led to a surge in research that examines the impacts of various dimensions of OCRs, such as volume, valence, variance, and sentiments on firm performance and/or product sales (Chevalier and Mayzlin 2006; Cui, Lui, and Guo. 2012; Kostyra, Reiner, Natter, and Klapper 2016). While early OCR research has provided an initial understanding of how the reviews can impact decision making and sales performance, recent benchmarking reports indicate that customers also place a heavy weight on marketing efforts by the firm (Burstein 2016). Consequently, research that focuses on OCRs and does not incorporate the influences of firm-initiated marketing efforts will not capture the complexity of online decision making nor will it accurately demonstrate the true impacts of OCRs and firm efforts.

Thus far, the vast majority of research into the effects of OCRs has dived into the characteristics of online reviews by examining the impact of OCR valence and volume largely independent of firm-initiated marketing efforts. Only a few studies have examined models that account for some type of interplays between OCRs and advertising (e.g., Gopinath, Thomas, and Krishnamurthi 2014; Moon, Bergey, and Iacobucci 2010) and discount strategies (Chong et al. 2016; Lu, Ba, Huang, and Feng 2013) on product performance. Unfortunately, these studies have been limited to examining static influences of OCRs and firm-initiated marketing efforts. They also consider only a few types of marketing efforts (i.e., advertising and discount). Collectively, such examinations render our understanding of OCRs and companies' marketing efforts incomplete, and likely lead to incorrect conclusions and faulty implementation. According to anchoring and adjustment theory, customers' perceptions based on previous information can be updated as new information varies (Dagger and Danaher 2014; Hibbert, Winklhofer, and Temerak 2012). Thus, failure to account for the relative impact of these drivers, as OCR availability grows from absence to full proliferation, does not allow for an accurate assessment of the effectiveness of firm-initiated marketing efforts across the span of the product lifecycle. Also, the narrow array of marketing efforts assessed in the OCR literature is unable to provide sufficient guidance for managers' daily business planning. Hence, without a dynamic assessment of a more inclusive set of marketing effects, as more OCR information becomes available, managers cannot have confidence in the effectiveness of their commonly used marketing efforts.

We seek to close these knowledge gaps by offering a comprehensive understanding of OCRs and companies' marketing efforts in predicting product sales. Specifically, our objective is to depict the true relationships (i.e., dynamic and non-linear) between OCR and a more inclusive suite of marketing actions, including the entire marketing mix—Price (discount), Promotion (free shipping), Product (product variety), and Place (multichannel offering)—in influencing customers' purchase decisions. To do so, we conduct two empirical studies via multiple research methods. Study 1 leverages daily observations from launch through product maturity (104 days after launch) for 252 fast fashion products. These data allow us to collect information on daily marketing efforts and sales as well as the evolution of OCRs from nonexistence to full proliferation. In Study 1, we develop an information-varying effect model (IVEM – assessing the impact of marketing efforts as each additional information (OCR) is made available to consumers) to capture the dynamic effects of firm-initiated marketing efforts with non-linear patterns, and, more importantly, quantify the OCR's importance in updating marketing efforts' effectiveness. In Study 2, we conduct an experiment to confirm the processes underlying the effects from Study 1. The consistency observed between the findings in Study 1 and Study 2 adds significant validity to our theoretical assertions.

The results of our research provide several contributions to the marketing literature. First, we extend existing research by moving beyond a core focus on discount and advertising by examining the impact of elements across the entire marketing mix on product sales. In doing so, we provide the most holistic insight into how a wide range of marketing tactics can impact sales in the presence of customer reviews. The results of our dynamic model demonstrate that the effectiveness of discount and free shipping are reduced, while the effectiveness of product variety and multichannel offerings are amplified when OCRs become available. Additionally, the effects of discount, product variety, and multichannel offerings have a limited duration. Specifically, we find that discount is significantly positive with a diminishing trend to the extent that once OCR volume reaches 49 instances, it is no different than zero. This diminishing trend derives from the fact that sufficient OCRs form a certain product perception for potential customers who then have confidence in their purchase decisions and thus reduce the need for the confidence built by price discounts to trigger their purchase decision. Similarly, the product variety and multichannel offering only impact sales when the number of OCRs ranges from 4 to 26 and from 15 to 55 instances, respectively. These results demonstrate not only significant contingencies on the effectiveness of marketing efforts on consumer spending but a comprehension of why the influences of marketing efforts are reduced as OCR availability increases, neither of which have been captured in prior research on OCRs. The consequence is that managers should not develop strategies based on static models and they should dynamically update marketing allocations as more OCR information becomes available.

In addition to the primary contributions offered by the dynamic model testing and additional marketing-controlled drivers, we also examine an important contingency related to the type of OCRs available to consumers. Specifically, we assess the differential effect of OCRs that are informative. Not all reviews are created equal and we demonstrate that reviews accompanied by informative qualitative comments have a differential impact on the effectiveness of marketing efforts. Ultimately, the results reveal that the management of online marketing efforts and the role that OCRs play in the decision-making process is far more dynamic than prior research leveraging static data suggests, and marketers can better predict product sales by properly accounting for the dynamic nature of these relationships.

Conceptual Background – Online Customer Reviews

The OCR literature has evolved considerably since initial studies in the mid-2000s. Early research in this space focused on establishing baseline effects of OCRs on product performance and concentrated on teasing out the relative roles of OCR volume, valence, and variance (e.g., Clemons, Gao, and Hitt 2006; Godes and Mayzlin 2004). Extending these early models, other investigations took a more nuanced view on the role of OCRs and examined the relative effects of particularly positive or negative reviews. For example, Chevalier and Mayzlin (2006) examined the effect of OCRs on sales of books at Amazon.com and Barnesandnoble.com, demonstrating that negative OCRs had stronger impacts on sales than positively valenced reviews. In another context, Clemons, Gao, and Hitt (2006) suggested that positive OCRs predict product sales growth better than negative OCRs, using beer industry data. More recently, researchers have enriched investigations by examining other dimensions like ratio of positive and negative reviews (Cui, Lui, and Guo 2012), review length (Zhang, Craciun, and Shin 2010), and reviewer experience (Yang and Mai 2010). Investigations like these helped establish the pervasive effects of OCRs and demonstrated the fact that not all OCRs are created equal.

The next evolution in the OCR literature was to better account for the impact of OCRs alongside other types of information (i.e., marketing activities). Initially these investigations explored the relative effects of OCRs and price discounts (e.g., Forman, Ghose, and Wiesenfeld 2008), but did not consider potential interplays between OCRs and other sources of information. From there, researchers considered a wider range of external information sources, including advertising (Gopinath, Thomas, and Krishnamurthi 2014; Moon, Bergey, and Iacobucci 2010), brand equity (Ho-Dac, Carson, and Moore 2013), and social media activity (Marchand, Hennig-Thurau, and Wiertz 2016), and also assessed the interplay between discount and OCR (Chong et al. 2016; Li and Hitt 2008; Lu et al. 2013). The investigations into the interplays between OCRs and other information sources suggest a consistent interaction with marketing efforts, and that these interactions can take on the form of substitute or complementary effects (Lu et al. 2013). Most recently, Chong et al. (2016) suggested that the interactions among OCR volume, sentiments, and discount are more important than the individual predictors themselves when forecasting product sales. Taken together, these studies demonstrate the importance of considering OCRs in parallel to other marketing activities and information sources.

In some of these interactive models, researchers demonstrated initial insight into the fact that marketing activities do not have constant effects but instead are contingent on the nature of OCRs. For example, Li and Hitt (2008) demonstrate the effects of price that vary with self-selection bias (average ratings of early reviews) to the extent that price exhibits higher impact on sales if the early buyers tend to like the products (i.e., positive self-selection bias), while price exhibits lower impact on sales if the early adopters tend to be critical about the products (negative self-selection bias). Building on these early results, a few other researchers have demonstrated time-varying impacts of OCRs across a product's life cycle (i.e., Gopinath, Thomas, and Krishnamurthi 2014; Marchand, Hennig-Thurau, and Wiertz 2016; Moe and Trusov 2011). These more recent investigations further highlight the dynamic nature of the effects that OCR plays in driving product sales.

The primary goal of our research is to comprehensively understand the interplays between OCRs and firm-initiated marketing efforts. As an overview, in Table 2-1 we summarize these earlier studies and outline the key themes in the OCR literature in accordance with our research goal. Specifically, in Table 2-1, we start by identifying the extent to which research adopted static or dynamic models, then the extent to which they assessed interplays between OCRs and elements of the marketing mix, and finally whether extant research has assessed why effects of marketing efforts change as OCRs vary by demonstrating the mediating process. In Table 2-1, we also outline the scope of our study relative to previous research.

Hypothesis Development

Anchoring and Adjustment Theory

We build our theoretical framework on consumer information search theory with a focus on anchoring and adjustment theory. According to consumer information search theory (e.g., Moorthy, Ratchford, and Talukdar 1997; Ratchford, Talukdar, and Lee 2007), consumers rely on various information sources to reduce their perceived uncertainty regarding whether a certain product fits their needs. Information sources can be classified based on channels, such that information gathered from one channel may decrease the amount of search consumers do on other channels (Ratchford, Talukdar, and Lee 2007). We categorize information sources by senders, such as marketing information sent by firms and user experience information shared by earlier adopters. These are primary information sources available to customers in our context.

Anchoring and adjustment theory was first proposed by Tversky and Kahneman (1974). They suggested that anchoring and adjustment is one type of heuristic that is employed in making decisions under uncertainty. They further assert that an adjustment from an anchor (a starting point) is normally implemented when a relevant value is available. This mental operation has been utilized in numerous studies where research presents how customers employ various sources of information sequentially during their decision making process (i.e., Dagger and Danaher 2014). More explicitly, people have a belief which can be adjusted by the impact of succeeding pieces of information (Dagger and Danaher 2014; Hogarth and Einhorn 1992). As the newly available information evolves over time, it is added to previous information held by people based on the anchoring and adjustment process, and eventually people make their decisions based on both the previous and the new information (Dagger and Danaher 2014; Hibbert, Winklhofer, and Temerak 2012).

Firm-initiated marketing efforts are available and their information richness is relatively invariant as soon as a product is commercialized, while OCR may become present at a later stage of a product life cycle and, more importantly, proliferate in terms of richness as a product matures. Thus, in this research, drawing on anchoring and adjustment theory, we articulate that while considering buying a product, consumers' beliefs or perceptions on firm-initiated marketing efforts regarding the product are updated or adjusted as OCR information availability evolves. More importantly, we postulate that the updates on the effects of firm-initiated marketing efforts may be non-linear in that OCR information is absent, present, and proliferates as a product ages. To provide a complete understanding on how the effects of companies' marketing efforts vary over levels of OCR information availability, we examine commonly used marketing strategies following the 4Ps Marketing Mix framework and depict how each of their impacts varies over the number of reviews. Explicitly, in this research, the firm-imitated marketing efforts contain Price (discount), Promotion (free shipping), Product (product variety), and Place (multichannel offering).

Interplays between OCRs and the Firm's Marketing Mix

Price (Discount). Regarding the relationship between discount and online reviews, the OCR literature offers support for both positive (Chong et al. 2016) and negative (Lu et al. 2013) interactions, effectively rendering current findings managerially inconclusive. However, neither the positive nor negative interaction studies considered the potential non-linearity when studying the interactions. Consequently, to reconcile the opposing findings and grasp the true relationship between OCR and pricing strategy, with respect to influencing product performance, we dig deeper and more comprehensively into the interaction by examining the non-linear effect of price discount as a function of OCR information availability.

As a backdrop to this non-linearity, vast research has suggested that products associated with higher discount rates stimulate more consumer demand (i.e., Chong et al. 2016; Raghubir 2004). During the pre-OCR period, customers evaluate new products primarily based on firm-initiated marketing efforts and perceive a lower price (higher discount) positively. However, they do not have alternative sources to judge the quality of the new products. During the post-OCR period, consumer-shared information (i.e., OCR) is deemed to be more credible and valuable to future consumers to judge product quality (Bickart and Schindler 2001). As uncertainty regarding the product decreases and confidence toward the final purchase decision increases due to the presence of OCRs, the same discount may become less appealing/necessary to future customers. These are customers who feel less sensitive about the price as they have made their decisions on whether to buy the product. This relationship can then be enlightened well by information substitution dynamics (Chen, Wang, and Xie 2011). Such dynamics assert that as more information from other sources (i.e., more OCRs) becomes available to customers over time, and, more importantly, the alternative source in our context is more credible than firm-initiated marketing efforts, customers will become more informed and form their attitudes towards a product. As this occurs, the first known information (i.e., price and discount) becomes less impactful. This substitute relationship is especially prominent when multiple sources of information aim to portray the same object. In our context, price and OCRs both offer information about the product itself. As such, Rao and Monroe (1988) have indicated that the price/discount (extrinsic cue) is less likely to have a significant effect on consumers' purchase decisions while other information about product attributes (intrinsic cues such as OCRs in our context) becomes dominant. In some cases, consumers are even willing to pay more if they are certain about the quality of the products through other sources (Ba and Pavlou 2002). This suggests that customers can become less price sensitive or price insensitive about products over time. Thus, we articulate the following.

H_1. The effectiveness of a price discount varies over levels of OCR's availability, with a decreasing trend.

Promotion (Free shipping). In e-commerce, free shipping is an important promotion tactic that firms can use to entice customers to make purchases (Chong et al. 2016). Such enticement of free shipping offers customer-based merits such as customer confidence and opportunity to "seize the moment" (Lantz and Hjort 2013). However, we assert that free shipping's positive impact on purchases also diminishes as OCRs accrue. Similar to our arguments regarding price (discount), we utilize the argument of information substitution dynamics to substantiate our free shipping premise (Chen, Wang, and Xie 2011). Specifically, as OCRs become more available to customers over time, customers will become more knowledgeable about the product with respect to its quality, fit, and attributes and then form their attitudes towards it. Additionally, OCRs are viewed as more credible than companies' marketing efforts. As such, the impact of the already known promotional information—free shipping—on customer purchase decisions declines. That is, free shipping becomes less important or appealing to customers when making purchase decisions.

H_2. The effectiveness of free shipping varies over levels of OCR's availability, with a decreasing trend.

Product (Product variety). It is well-known that customers oftentimes have heterogeneous preferences for product attributes. To cope with this situation, firms offer a variety of options to satisfy customers' heterogeneous needs, build customer confidence that he or she is able to find what fits their needs, and augment firm performance (Mendelson and Parlakturk 2008). Product variety has been measured in different ways, such as the number of brands in a market and the number of models in a product group/line (i.e., Chen, Eliashberg, and Zipkin 1998; Lancaster 1990). Since the focal interest in our research is at product level and we aim to understand drivers of product success, we utilize the number of options (i.e., the multiplication of the number of colors and that of sizes) offered by a product as the parallel proxy for product variety. Interestingly, the good intention of product variety is not always well received by customers. Various offers do not transfer greater value to customers and variety may even cause unwanted complexity and information overload (Dellaert and Stremersch 2005), leading to more confusion for prospective customers and eventually making any personalization effort ineffective (Iyengar and Lepper 2000; Ricotta and Costabile 2007). This situation is more severe during the pre-OCR time period. Due to the limited availability of information, future customers also perceive substantial uncertainty about the product quality and fit. Thus, the synergy between confusion and uncertainty may impede customers from recognizing the good intention of companies' offering product variety.

At the start, once OCRs are posted by early adopters, the risk and uncertainty associated with the product is decreased. Then, when customers are assured of the quality and fit of the product, they start valuing the variety offered by the product and select the options they prefer. In this scenario, we posit that the good intention of product variety is more likely to be recognized by customers after OCRs become available. However, drawing on the informational cascades literature, the gradually formed informational cascades may lead prospective customers to adopt the options(s) that have been recommended by others despite of their own preferences (Bikhchandani, Hirshleifer, and Welch 1992). Product variety also becomes less informative and influential to customers as more OCRs are accumulated. Abundant OCR information suggests to customers what options are good and potentially right, creating increased confidence to make customer decisions.

H_3. The effectiveness of product variety fluctuates over levels of OCR's availability, initially with an increasing trend and then moving to a decreasing trend.

Place (Multichannel offering). Many firms operate in both online and offline settings. Broadly, the offline setting provides customers an opportunity to touch and feel the product before purchasing while the online setting offers convenience and low search cost (Lynch and Ariely 2000). Due to the inability to touch/feel product online, customers perceive more uncertainty and less confidence (D'Alessandro, Girardi, and Tiangsoongnern 2012; Ofek, Katona, and Sarvary 2011). Thus, when shopping online, knowing that a product is also offered offline (multichannel) can add confidence and reduce uncertainty for customers, because in this scenario, firms can invite customers to try products in a local store (Tang and Xing 2001). Yet, this dual online/offline benefit is not revealed all the time. When there is no alternative source to assess product quality, such as OCRs, customers may choose to visit an offline store to buy the product. Alternatively, those who have no access to stores may wait until they are certain about the product, such as when OCRs indicate someone has tried the product offline.

However, when OCRs start accumulating, the multichannel's impact is revealing. Prospective customers may decide to buy the product online since others have purchased the products and have indicated that they tried on the product in the physical store. Such OCRs add trustworthiness and, thus, multichannels become compelling to customers. For those who have access to physical stores, they feel more inclined to make the purchase online due to the lower search cost. For those who have no access to physical stores, OCRs help them realize the extra confidence about the product added by multichannels. Drawing on information substitution dynamics, when there are abundant OCRs (i.e., customers receive sufficient information about the product quality, fit, and features), a multichannel offering, as a supplementary piece of information adding confidence toward the product, may become less effective.

H_4. The effectiveness of a multichannel offering varies over levels of OCR's availability, initially with an increasing trend and then moving to a decreasing trend.

The literature also discusses various dimensions of OCR and shows that they are predictors of OCR's persuasion on customers' decisions (i.e., Chevalier and Mayzlin 2006; Kostyra et al. 2016). In effect, not all OCRs are created equal. We further articulate that given the same total amount of OCR information, information availability of persuasive OCRs (i.e., informative OCRs) can further alter the effectiveness of a firm's marketing efforts. That is to say, not only does information quantity matter, information quality—how powerful the information is—is also significant. Thus, to understand the dynamic interplays between OCR and companies' marketing efforts thoroughly and to be able to deliver substantial managerial implications, we consider persuasive or powerful OCRs, that is *informative* OCRs, in addition to total OCRs.

We postulate that reviews that contain concrete information are more informative and persuasive than general and generic reviews. For example, a generic review such as "it is a good product" is a lot less informative or persuasive than a specific review such as "the size is accurate, material is kind of thick so it is good for spring or fall. Good product". In line with this logic, Goldfarb and Tucker (2011) suggest that reviews with more solid and detailed information are more vivid, and De Vries, Gensler, and Leeflang (2012) further indicate that vivid posts can impart more influence to audiences than less vivid posts. Consequently, informative/vivid OCRs will have greater impact than standard reviews. Informative OCRs help prospective customers develop a thorough comprehension of the product more efficiently than regular OCRs, thus reducing the effectiveness of price and free shipping more quickly. Also, due to the high vividness and information density of these OCRs, product variety and a multichannel offering generate positive impact on sales and then become ineffective more rapidly.

$H_{5a\text{-}b}$. The effectiveness of a price discount (H_{5a}) and free shipping (H_{5b}) varies for levels of *informative* OCR availability to the extent that the decreasing trend is steeper.

$H_{5c\text{-}d}$. The effectiveness of product variety (H_{5c}) and a multichannel offering (H_{5d}) varies for levels of *informative* OCR availability to the extent that the increasing and decreasing trends are steeper.

Mediating Process

To complete the understanding that the effectiveness of companies' marketing efforts varies over levels of OCR availability, we aim to cognize the underpinning of the above relationships. The obstacle that customers face before they decide to place an order is that they (often) do not have adequate confidence in their purchase decision. This can create a significant hurdle in making the purchase decision. Lack of confidence can be a particularly strong barrier to purchase when consumers have limited experience with a product (Bart, Shankar, Sultan, and Urban 2005; Hongyoun Hahn and Kim 2009).

In an effort to overcome these consumer confidence barriers, marketers engage in a series of tactics to increase confidence that the purchase is a good decision. For instance, offering free shipping can increase customer confidence and offer the opportunity to "seize the moment" (Lantz and Hjort 2013) and price discounts are useful cues for customers that aid in cognitive evaluations of products and purchase decisions (Raghubir 2004). However, OCRs provide an alternative information source to help prospect customers evaluate products. This OCR source is also viewed as more credible than firm-initiated marketing efforts (Bickart and Schindler 2001), a supposition that can be particularly effective in developing trust online (Benedicktus, Brady, Darke, and Voorhees 2010). In addition, OCRs can deliver more detailed information about the product. When viewing online reviews, customers are exposed to what is oftentimes considered highly credible information on the product's quality, features, fit, and comparison to the competitive alternatives. Hence, as the objective and detailed information from OCRs accumulates, such sheer amount of information reduces uncertainty about the product and creates confidence in customers' purchase decisions.

Taken together, both companies' marketing efforts and OCRs can directly increase customer confidence in a purchase decision, which ultimately drives future purchase behavior. However, given the objective and comprehensive information offered by OCRs, we argue that the indirect effect of companies' marketing efforts, via confidence on purchase decisions, may be mitigated as OCRs accumulate. In other words, as consensus information via online reviews accumulates, the effects of companies' marketing efforts are diminished (Benedicktus et al. 2010).

H_6. The effect of marketing efforts on product sales is mediated by customer confidence and this indirect effect decreases as level of OCR availability increases.

Study 1

To test the hypotheses, we conduct two studies using different research methods. In Study 1, we collect fast fashion product data from Tmall, operated by the Alibaba Group, and demonstrate how effectiveness of companies' marketing efforts is shaped dynamically and non-linearly across levels of OCR availability. Later on, utilizing an experiment, Study 2 empirically demonstrates the underlying mechanism (confidence) that transfers the impact of companies' marketing efforts to product sales. Study 2 also reveals that these indirect effects are alleviated as OCRs accumulate. Additionally, Study 2 validates the findings in Study 1 under a more controlled environment.

Data and Variables

For Study 1, the data we use is from Taobao Mall (Tmall.com), the largest B2C online retailer operated in China by the Alibaba Group. Tmall is a sales and marketing platform for local Chinese as well as international business entities to sell brand-name goods to consumers in China. According to Alexa Internet, Tmall was the 18th most visited website globally and the 7th in China. iResearch Consulting Group also reported that China has become the largest B2C e-commerce market in the world and Tmall had 61.4% of the Chinese market, followed by JD.com with an 18% market share. Given Tmall's leading role in B2C e-commerce, our investigation of the products commercialized on Tmall.com adds state-of-the-art findings and implications that are relevant for marketing strategy, consumer behavior, and global strategy (cf. Kozlenkova et al. 2017).

We use fast fashion product data in this study. This context ensures that we can rigorously study the dynamic interplays of the two information sources (user generated content and firm-initiated marketing information) on product performance largely without several potential confounding factors that other product scenarios would contain. Most fashion firms on Tmall launch products every other day or at least every week. For example, Forbes reported that Zara delivers new products at least twice each week on the platform, adding up to 10,000 new designs each year (Petro 2012). Given the high-speed context and relatively short product life cycles, these firms rarely employ traditional advertisements or pre-launch activities for a specific product, resulting in nearly no online word of mouth (i.e., tweets) generated for a given product outside the product webpage. Nevertheless, these firms do take advantage of advertisements to broadcast brands and enjoy brand-level WOM. Consequently, the primary information that prospective customers are able to draw inferences from while making purchasing decisions is firm-initiated marketing efforts communicated on the Tmall marketplace and OCRs on the product webpage, thus providing a clean empirical setting for studying our research hypotheses. We collected data on 252 products across 12 popular brands in this industry for 104 days, starting from their first launch dates. The first launch dates included in our study are from May 16-30, 2017. The data include information on both firm-initiated marketing efforts and OCR characteristics. The focal firm-initiated marketing efforts contain price discount, free shipping, product variety, and multichannel offering. OCRs normally become available to potential customers a few days after the first launch dates (mean = 10.89 days in our sample). We also collected the OCRs' characteristics, such as volume, cumulative valence, and review content.

Tmall does not share individual rating/valence for each review. To form informative OCRs and variance of OCRs, two coders separately coded the valence of each review and resolved the disagreement by discussing with a third coder. During the coding process, we asked the coders to list all the categories/themes in the reviews and gave separate valence ratings on a seven-point scale for each category (1 being the extremely negative and 7 being extremely positive). The average valence across categories of a review was calculated as the valence of that review. Then, we computed variance of reviews based on coded individual valence of reviews available to customers on a given day for a product. Specifically, following the categorization process suggested by Lincoln and Guba (1985), two coders identified the repetitive themes (i.e., shipping quality and design style) by listing items that manifested similar characteristics. After carefully reading each review, each coder first listed all unique items of a review and then classified items into categories or themes which "are defined in such a way that they are internally as homogeneous as possible and externally as heterogeneous as possible" (Lincoln and Guba, 1985, p. 349). This categorization process was reiterated a few times until categories were formed cleanly and solidly. Then the coders compared their identified themes and the corresponding representative items. The level of agreement between the two coders in data coding was 90 percent. The differences were resolved by discussing with the third coder. Ultimately, seven categories were established: product design, product price, emotion toward brand, shipping, online service, accuracy of description, and product quality. To be an informative OCR, it needs to contain information of at least one category stated above. 72.94% of the coded OCRs (6,981 reviews) are informative reviews and the rest are generic.

To eliminate potential confounding effects, we also incorporate brand-, product-, and OCR-level covariates in the models. For example, fast fashion firms deploy various advertisements across brands, and as discussed, they do not launch any advertising campaign for a certain new product due to the short product life cycle and highly frequent new product launches. Thus, eliminating the normal brand-level advertising effect effectively removes the potential for an advertising confounding effect. To do so, we control brand dummy variables in the model. We include maturity (the number of days a product has been in market) to eliminate the confounding effect of product maturity. We include lagged total unit sales in the model to control for the effect of any persistence. Also, we control cumulative valence and variance of reviews for each product. We utilize the cumulative valence displayed on the product page on Tmall, as it is more visible to prospective customers than the coded individual valence we have. Table 2-2 presents more details on the included variables' operationalization. Finally, to test our hypotheses, we need to first demonstrate how effectiveness of companies' marketing efforts varies before and after OCRs become available as benchmarks. Hence, we summarize these correlations and descriptive statistics in Tables 2-3 and 2-4 for the pre-OCR dataset (sample size: 2,492) and the post-OCR dataset (sample size: 21,340), respectively.

Model Development

We conduct three sets of analyses to examine the hypotheses. First, as benchmarks, we aim to understand the differential impacts of firm-initiated marketing efforts before and after OCRs become available. We estimate two baseline models without any varying effects using mixed-effect models. One is for the observations during pre-OCR and the other one is for the observations during post-OCR. The reason for using a split-sample approach rather than using interaction terms is that we include two important covariates (OCR valence and variance) in the post-OCR model to receive more rigorous parameter estimates of the variables of interest; however, these two variables are not applicable to the pre-OCR model.

Then, using the post-OCR dataset, we assess H_1 to H_4 regarding the effectiveness of companies' marketing efforts varying over levels of OCR's availability. To capture the accurate non-linearity in the interactions between OCR volume and firm-initiated marketing efforts, we develop the information-varying effect models (IVEM) with random slopes. In our model, the effect of marketing efforts is a function of cumulative OCR volume for time $_j$ and product *i*. Specifically, we use regression splines (cubic splines) to capture the potential non-linearity in the interaction effects. Cubic spline is commonly used in marketing research and is effectively flexible (Kumar, Choi, and Greene 2017). Our approach is analogous to that of the time-varying effect model (TVEM), thus offering an appropriate approach to uncover the shape of coefficient functions using the data without assuming parametric functions (for a comprehensive description on TVEM, see Saboo, Kumar, and Park 2016 and Tan et al. 2012). Rather than assuming constant parameter estimates (such as in the baseline model), our IVEM allows the coefficients of linear regression models to vary smoothly as a function of the OCR volume variable, demonstrated in Equation 1.

$$ln(S_{ij}) = \beta_0(v_{ij}) + \beta_1(v_{ij})X_{ij} + \varepsilon_{ij}; \quad i = 1, \ldots, n, j = 1, \ldots, m_i \quad (1)$$

where $\ln(S_{ij})$ is the outcome variable for subject *i* at time *j* (log of daily product sales in our context), X_{ij} is the firm-initiated marketing efforts (i.e., discount) for subject *i* at time *j*, n represents the total number of subjects (the total number of products in our context), m_i is the number of repeated observations for subject *i* (days on market in our context), v_{ij} is the cumulative OCR volume at time *j* for subject *i*, $\beta_0(v_{ij})$ and $\beta_1(v_{ij})$ are assumed to be the continuous coefficient functions (i.e., cubic splines) that vary over volume v_{ij} (shown in Equations 2 and 3, respectively), and random errors ε_{ij} are assumed to be normally and independently distributed. Then, the IVEM becomes Equation 4.

$$Intecerpt: \beta_0(v_{ij}) = \alpha_0 + \alpha_1 v_{ij} + \alpha_2 v_{ij}^2 + \alpha_3 v_{ij}^3 + \sum_{k=1}^{K} \alpha_{3+k} (v_{ij} - \tau_k)_+^3 \quad (2)$$

$$Coefficient\ of\ X_{ij}: \beta_1(v_{ij}) = b_0 + b_1 v_{ij} + b_2 v_{ij}^2 + b_3 v_{ij}^3 + \sum_{k=1}^{K} b_{3+k} (v_{ij} - \tau_k)_+^3 \quad (3)$$

$$ln(S_{ij}) = \alpha_0 + \alpha_1 v_{ij} + \alpha_2 v_{ij}^2 + \alpha_3 v_{ij}^3 + \sum_{k=1}^{K} \alpha_{3+k} (v_{ij} - \tau_k)_+^3 + b_0 X_{ij} + b_1 v_{ij} X_{ij} + b_2 v_{ij}^2 X_{ij} + b_3 v_{ij}^3 X_{ij} + \sum_{k=1}^{K} b_{3+k} (v_{ij} - \tau_k)_+^3 X_{ij} + \varepsilon_{ij} \quad (4)$$

where K represents the total number of knots. The knots are referred to as τ_k (k=1,…,K). $(v_{ij} - \tau_k)_+^3$ indicates the third degree truncated power function, and $\sum_{k=1}^{K} \alpha_{3+k}$ and $\sum_{k=1}^{K} b_{3+k}$ are the coefficients of the truncated power function and act as penalty coefficients. For a comprehensive description of the P-spline method, see Kumar, Choi, and Greene (2017).

To empirically examine H_5 on the varying effectiveness of companies' marketing efforts as functions of the volume of informative OCRs, we adjust the stated IVEM and replace the OCR volume (v_{ij}) with the informative OCR volume ($v_{ij}^{informative}$) while accounting for v_{ij} in the model. Before building the models, we need to account for issues that may bias our estimation approach, specifically the endogeneity of firm-initiated marketing efforts and OCR volume.

Assessing Endogeneity

With respect to endogeneity, price discount and free shipping are potentially endogenous. Firms may adjust their current discount and whether to offer free shipping to customers for a certain product based on the previous performance indicators of that product. However, product variety and the multichannel offering are most likely determined before the product is launched, and thus is exogenous. Following Chintagunta, Gopinath, and Venkataraman (2010) and Kumar et al. (2013), we also consider OCR volume to be endogenous in our research. We utilize a control function approach to model the potential endogeneity of the above three variables using two-stage estimation (i.e., Petrin and Train 2010; Saboo, Kumar, and Park 2016). At the first stage, we regress the endogenous variables on a set of exogenous variables that are identified as instrumental variables (IVs). Following Kumar, Choi, and Greene (2017), we include the change in sales ($\Delta \ln(S_{ij})$) and the focal endogenous variables in the previous two days, as instruments to control for the potential endogeneity of discount and free shipping, shown in Equation 5 and 6, respectively. Managers may evaluate the growth in sales in the previous periods and determine the levels of marketing efforts for the current time period. Also, the past change in sales is not assumed to be related to current sales (Roodman 2009). Growth in the endogenous variables is not related to current sales but captures the changing trends in the endogenous variables. Thus, these variables meet the relevance and the exclusion criteria of being good IVs. Further, Chintagunta, Gopinath, and Venkataraman (2010) suggest that weather conditions can be good IVs to control the potential endogeneity of OCR volume. Following their suggestions, we include daily weather conditions (i.e., sunny day, cloudy day, levels of wind, and highest temperature of the day) in eastern, western, northern, southern, central, northeastern, and southwestern China, as instruments in Equation 7.

$$discount_{ij} = z_{ij}^{discount}\lambda^{discount} + \eta_{ij}^{discount} \qquad (5)$$

$$\ln\left(\frac{P(fs_{ij})}{1-P(fs_{ij})}\right) = z_{ij}^{fs}\lambda^{fs} + \eta_{ij}^{fs} \qquad (6)$$

$$v_{ij} = z_{ij}^{v}\lambda^{v} + \eta_{ij}^{v} \qquad (7)$$

where *fs* is the abbreviations of free shipping, $P(fs_{ij})$ is the probability that subject *i* offers free shipping at time *j*, $\lambda^{discount}$, λ^{fs}, and λ^{v} are the unknown parameter vectors, $z_{ij}^{discount}$, z_{ij}^{fs}, and z_{ij}^{v} are the vectors of IVs specified earlier, and the random errors $\eta_{ij}^{discount}$, η_{ij}^{fs}, and η_{ij}^{v}.

We employ the random effect models with cluster robust standard errors to estimate Equations 5 and 7 and obtain the consistent estimates of $\lambda^{discount}$ and λ^{v} and then use the residuals $\widehat{\eta_{ij}^{discount}}$ and $\widehat{\eta_{ij}^{v}}$ as the additional explanatory variables in the second stage (shown in the full model in Equation 8). For Equation 6, because free shipping is a dummy variable, we utilize the pooled Probit model to estimate the equation. To obtain the accurate residuals of free shipping that can be used in the second stage, we transform $\widehat{\eta_{ij}^{fs}}$ calculated from Equation 6 to generalized residuals $\widehat{\delta_{ij}^{fs}}$ and insert $\widehat{\delta_{ij}^{fs}}$ in the full model (shown in Equation 8). Table 2-5 shows the first-stage results of our control function approach that account for the potential endogeneity of discount, free shipping, and OCR volume. Finally, we specify our final model in Equation 8 to test H_1 to H_4.

$$\ln(S_{ij}) = \beta_0(v_{ij}) + \beta_1(v_{ij})discount_{ij} + \beta_2(v_{ij})fs_{ij} + \beta_3(v_{ij})pro\_variety_i +$$

$$\beta_4(v_{ij})multichannel_i + \beta_5 l\_totalnit_{ij} + \beta_6 valence_{ij} + \beta_7 variance_{ij} + \beta_8 holiday_{ij} +$$

$\beta_9 maturity_{ij} + \beta_{10} weekend_{ij} + \beta_{11} org\_price_i + brand_{dummies}\lambda^{brand} + \ +\gamma_1 \eta_{iJ}^{\widehat{discount}} +$

$\gamma_2 \widehat{\delta_{iJ}^{fs}} \quad + \gamma_3 \widehat{\eta_{iJ}^{v}} + \ \varepsilon_{ij} \quad (8)$

where $discount_{ij}, fs_{ij}, pro\_variety_i, and\ multichannel_i$ represent the companies' four Ps marketing efforts and the random errors ε_{ij}. Table 2-2 shows the definition of each variable.

Results

Baseline Models without Information-Varying Effects. The results of the baseline models[7] (shown in Table 2-6) suggest that discount has a positive and significant static effect on product sales during the pre-OCR period and the effect is alleviated during the post-OCR period ($\beta_{before} = 0.562$, $p < .05$; $\beta_{after} = 0.307$, $p < .001$). We also find that free shipping has a significant and positive impact on product sales during the pre-OCR period and generates a less positive impact during the post-OCR period ($\beta_{before} = 1.027$, $p < .001$; $\beta_{after} = 0.721$, $p < .001$). Also, our results indicate that product variety and the multichannel offering fail to affect product sales significantly during the pre-OCR period ($\beta_{pro\_variety\_before} = 0.032$, $p > .10$; $\beta_{multichannel\_before} = 0.022$, $p > .10$). However, product variety's influence becomes positive and significant during the post-OCR period ($\beta_{pro\_variety\_after} = 0.121$, $p < .01$). The multichannel offering does not affect product sales in the post-OCR baseline model, but the sign of the parameter is positive ($\beta_{multichannel\_after} = 0.087$, $p = .16$). Collectively, the benchmarking effects of marketing efforts before and after OCRs' availability are generally consistent with H_1-H_4. And, we find that the signs of the covariates' coefficients are plausible.

[7] To demonstrate the existence of endogeneity issues of discount, free shipping, and OCR volume, we re-ran both baseline models without the control functions' residuals and compared the results to those with the endogeneity controls in Table 2-Appendix. The AIC, -2RLL, and estimated parameters all indicated the necessity of endogeneity controls.

IVEM over Volume of OCRs and Informative OCRs. The model results for the IVEM are presented in Figures 2-1 and 2-2. Table 2-7 presents the model fit comparisons between the baseline model for the post-OCR period, monotonic information-varying parameter model (i.e. the effect of companies' marketing efforts varies over levels of OCR availability linearly), and IVEM. The results indicate a moderately improved model fit of IVEM relative to the other two models. In addition to the improved model fit, this model contributes significantly to the theoretical understanding of OCRs' impact and managerial implications (see details in the discussion section). The results of IVEM based on overall OCR volume, in general, suggest that the effectiveness of the four Ps marketing efforts varies as a function of cumulative volume of OCR with non-linear patterns. Further, although the results of IVEM based on volume of informative OCRs overall indicate similar patterns to the results from the model based on overall OCR volume, the non-linear patterns do show some key differences across the marketing efforts. To maintain interpretability of the findings, we solely present the effects of marketing efforts over the levels of OCRs availability up until two standard deviations (SD) above the average number of OCRs.

Discount. As shown in Figure 2-1 (A1), the results indicate that the effectiveness of the discount is positive with a diminishing trend. This positive impact becomes insignificant when the number of OCRs is equal to or greater than 49 ($\beta_{OCR=49} = 0.191$, $p > .05$). The positive impact of the discount diminishes as OCRs accrue, in accordance with H_1. Figure 2-1 (A2) demonstrates that if the cumulative volume of *informative* OCRs achieves 39 ($\beta_{OCR=39} = 0.190$, $p > .05$) or more, a discount no longer affects product performance. The discount effect varies with a steeper decreasing trend, compared to the decreasing trend presented based on the levels of overall OCR volume, supporting H_{5a}. Consequently, it takes fewer *informative* OCRs to offset the positive impact of a price discount.

Free shipping. Figure 2-1 (B1) shows that the effectiveness of free shipping on product sales is consistently positive but lower than that in the pre-OCR period ($\beta_{before} = 1.027$, $p < .001$). Noticeably, at the end of observation period, the effect exhibits a flattening trend when the effect is roughly 0.80, which is still lower than the pre-OCR levels. After the free shipping effect experiences an initial dip (lowest point $\beta_{OCR=8} = 0.613$, $p < .05$), it recovers and plateaus at the range of 0.800-0.810. Thus, the pattern of results provides support for H_2. Additionally, free shipping's effectiveness also persists to be positive and significant with a decreasing trend and then a flat trend over the spectrum of *informative* OCR volume. It reaches the lowest value of 0.617 when there are 6 *informative* OCRs (see Figure 2-1 (B2)) and stays at the range of 0.840 to 0.850. Overall, the effectiveness of free shipping varies with a steeper decreasing trend followed by a flat trend, compared to the trend based on the levels of overall OCR volume. Thus, H_{5b} is supported.

The reason that the free shipping effect persists across the entire range of OCRs when the price discount effect does not is likely due to the differential role that each plays in the customer's decision making process. Unlike changes in product prices, changes in the shipping fee are not directly associated with product quality (Ding, Ross, and Rao 2010). Shipping discounts can increase confidence in the purchase decision by reducing financial risk, without the accompanying increase in performance risk that would be associated by price discounts. Because of this strong role in driving customer confidence, its influence likely cannot be completely substituted with OCRs.

Product variety. The results shown in Figure 2-2 (A1) reveal that the effect of product variety becomes positive on product sales when the number of OCRs is 4 ($\beta_{OCR=4} = 0.115$, $p < .05$). This effect then reveals an inverted U shape with the maximum effect reaching 0.132 when the number of OCR equals to 10. As the number increases and reaches 27 or above, product variety imposes no effect on product sales ($\beta_{OCR=27} = 0.093$, $p > .05$). Consistent with H_3, the effect of product variety becomes positive following an increasing and then a decreasing trend as more OCRs are available to prospective customers. Figure 2-2 (A2) also demonstrates an inverted U-shaped pattern for the effectiveness of product variety as it only impacts product performance when the number of *informative* OCRs is between 3 ($\beta_{OCR=3} = 0.110$, $p < .05$) and 21 ($\beta_{OCR=21} = 0.105$, $p < .05$). The result is consistent with H_{5c}. More explicitly, it takes a smaller number of *informative* OCRs to make the positive impact of product variety prominent and it also takes fewer *informative* OCRs to offset its positive effect.

Multichannel offering. The results shown in Figure 2-2 (B1) reveals that the effect of the multichannel offering becomes positive and significant on product sales when the number of OCRs is 15 ($\beta_{OCR=15} = 0.141$, $p < .05$). This effect then reveals an inverted U shape with the maximum effect reaching 0.238 when the number of OCR equals to 40. As the number increases and reaches 56 or above, multichannel offering imposes no effect on product sales ($\beta_{OCR=56} = 0.219$, $p > .05$). In accordance with H_4, the effect of the multichannel offering becomes positive following an increasing and then a decreasing trend as more OCRs are available to prospective customers. Then, Figure 2-2 (B2) reveals that the multichannel offering only impacts product performance when the number of *informative* OCRs is between 9 ($\beta_{OCR=9} = 0.131$, $p < .05$) and 45 ($\beta_{OCR=45} = 0.255$, $p < .05$). Overall, the results are consistent with $H_{5d.}$ That is, it takes a smaller number of *informative* OCRs to make the positive impact of the multichannel offering prominent and it also takes fewer *informative* OCRs to offset its positive effect.

Study 2

The main purpose of Study 2 is to test H_6, which states that the underlying mechanism that transfers the impact of companies' marketing efforts to product sales is customer confidence in the purchase decision and that these indirect effects are diminished as OCRs accumulate. To test this hypothesis, we use a 3 (OCR Volume: No Volume, Medium Volume, High Volume) × 2 (Price Discount: No Discount, Discount) between-subjects experimental design. Rather than attempting to simultaneously manipulate the effects of four marketing mix elements alongside OCRs in a single experiment, we selected price discounts as an exemplar marketing effort for the sake of the process investigation. Price discounts are commonly used in experimental scenarios and were demonstrated to be a strong marketing action in the first study.

Participants and Procedure

Participants, recruited on Amazon Mechanical Turk, included 235 adults (55% female) with an average age of 37 years. In this study, to enhance the generalizability of our research, we collect data on customers' purchase intention of a TV product, which differs from fast fashion products used in Study 1. TVs are a search product with high economic value (the price for the TV is $899.99 in the experiment), whereas fast fashion products are experiential products with relatively low economic value (the average price is $55.81 in Study 1). Specifically, participants were conditioned to be in the market for a new HDR TV. While searching on a popular ecommerce site, they came across a product that appeared to meet their technical specifications. Then, they were presented with information about the TV in addition to pricing and customer review information.

For the OCR volume manipulation, the no OCR condition displayed “there are no customer reviews yet,” for the medium volume there were 403 reviews with an average rating of 4.8, and for the high volume there were 1,203 reviews with an average rating of 4.8. The OCR volume levels were set based on the current count of reviews for HDR TVs produced by TCL on Amazon (the focal brand used in the experiment). Specifically, the medium condition takes the average number of reviews of TCL TV products and the high condition takes the sum of the average and two SD of the numbers of reviews. For the price discount manipulation, the no discount condition simply indicated the list price of the television at $899.00 with no discount. For the discount condition, we presented both the list price and a sale price of $577.92 (suggesting a 36% discount). The discount level was set based on comparable percentage of the discounts we observed in Study 1.

Each participant was randomly assigned to one of the six conditions and was first exposed to the manipulations, then measures of purchase intent, followed by measures of the mediator (customer confidence), and we closed the survey with manipulation checks and demographics. Purchase intention was measured with a single item from Perkins and Forehand (2011) that read: “How likely would you be to purchase this product?” on a seven-point scale. Customer confidence was measured using three items adapted from Argo, Dahl, and Manchanda (2012). The items assessed the extent to which consumers felt purchasing the TV would be a good decision followed by items (measured on a seven-point scale where 1 = Not at All and 7 = Extremely) that included “confident,” “certain,” and “sure.”

Results

The manipulations worked as expected. Specifically, for the price discount manipulation 97.4% of the participants recalled if the product was being sold at a discount (or not). For OCR volume, participants had awareness of OCR volume and recalled the number of reviews that were presented ($M_{No\ Volume}$ = 0.68 Reviews; $M_{Medium\ Volume}$ = 375 Reviews; $M_{High\ Volume}$ = 1,226 Reviews). To test H_6, we conduct two related analyses. First, we conduct a demonstration of the main and interaction effects on customer confidence using ANOVA and simple effects comparisons. Then, we assess mediation using the PROCESS macro to assess the extent to which the indirect effect of price discounts on purchase intentions is moderated by OCR volume.

The results of a 2 (price discount) x 3 (OCR Volume) ANOVA with customer confidence as the dependent variable revealed significant main effects for both the fixed factors and an interaction between price discount and OCR Volume. Customer confidence was higher when price discounts were offered ($M_{No\ Discount}$ = 4.27; $M_{Discount}$ = 4.99; $F = 14.44$, $p < .01$) and when OCRs were provided ($M_{No\ Volume}$ = 3.46, $M_{Medium\ Volume}$ = 5.23; $M_{High\ Volume}$ = 5.20; $F = 37.53$, $p < .01$). The interaction effect ($F = 3.45$, $p < .05$) demonstrated that the effect of the price discount was significantly reduced as OCR volume increased. To formally test this pattern, we conducted simple effects tests within each OCR volume condition. The results revealed that price discounts had a significant effect on confidence in the “No OCR Volume” condition, but this effect was not significant in the two conditions when OCR volume was present. We plot these mean differences and standard error bands across both sets of manipulations in Figure 2-3. These results provide initial support for H_6, and we continue by formally examining the extent to which price discounts indirectly affect purchase intentions and the degree to which OCR volume moderates this effect using the PROCESS macro (Hayes 2012; model 7).

To formally test the moderated mediation, we first recoded the three-condition OCR volume variable into a two-condition variable where 0 = No OCR Volume and 1 = OCR volume condition that combined the medium- and high-volume OCR groups. This allowed us to test the extent to which the effects of the price discounts changed in the presence of customer reviews. Using this variable along with the price discount condition (0 = no discount; 1 = discount), customer confidence, and purchase intentions, we ran PROCESS Model 7 with 10,000 bootstrap samples and bias-corrected, 95% confidence intervals.

We find direct effects of price discounts ($\beta_{discount}$ = 1.41, CI = [0.86, 1.96]) and OCR volume ($\beta_{OCR\ Volume}$ = 2.27, CI = [1.81, 1.96]) on customer confidence. In addition, the interaction between these variables was significant ($\beta_{interaction}$ = -1.03, CI = [-1.70, -0.36]) and the sign suggests that the effects of the price discounts are reduced in the presence of OCRs. With respect to mediation, the conditional, indirect effects of price discounts on purchase intentions through confidence were significant ($\beta_{No\ OCR\ Volume}$ = 1.21, CI = [0.64, 1.69]; $\beta_{OCR\ Volume}$ = 0.32, CI = [0.06, 0.63]), demonstrating that confidence mediates the effects of price discounts on purchase intentions. Finally, results of the moderated mediation analysis demonstrate that the significant indirect effect is moderated by OCR volume (-0.88, CI = [-1.51, -0.26]) to the extent that the effect of the price discounts on purchase intentions is significantly reduced in the presence of OCR information. Collectively, these results provide support for H_6 (with complete results in Table 2-8).

Discussion

The results of the information-varying effect model demonstrate a significant interplay between OCRs and companies' marketing efforts, and reveal that these interactive effects are dynamic and non-linear in nature. Consequently, these results using large-scale data (Study 1) and conditioned follow-up analyses (Study 2) seriously question the validity of prior research on the topic. Specifically, prior research that focused on static designs likely has underestimated the true nature of the moderating effects of OCRs on marketing outcomes. Our results suggest that the manner in which consumers integrate and weight OCRs versus company-driven marketing information is substantially more complex than prior studies would suggest to the extent that the significance of the effects of all four Ps marketing mix variables (discount, free shipping, product variety, and multichannel offering) is contingent on the volume of OCRs. Thus, the resource allocation across various marketing mix variables as well as the maximizing of benefits of employed marketing tactics must be managed dynamically across the product lifecycle.

Surprisingly, we find that free shipping's influence on product sales is reduced as OCRs become available, yet is immune to OCR evolvement and maintains a relatively stable level as more OCRs become handy. For product variety and the multichannel offering to impart their impacts on product performance, some OCRs are an essential condition and their impacts fade out as OCRs become abundant. Our research is also able to show that the above varying effects of companies' marketing efforts stem from the fact that indirect effects of these marketing efforts via confidence are diminished as OCRs accumulate. Sufficient OCR information enables potential customers to form a certain perception of the product and make a trusted purchase decision. Effectively, in this case, the contribution of company-initiated marketing efforts to enhancing customer confidence becomes needless as customers may have made their decisions based on OCRs. These new insights have significant theoretical contributions and managerial implications.

Theoretical Contributions

Our research enriches marketing theory, especially with respect to consumer search and utilization of information while making purchasing decisions. Taking advantage of two studies via diverse methods provides a strong empirical demonstration that consumers actively update their evaluations of a brand/product as new information becomes available. Consistent with anchoring and adjustment theory, when customers are able to access more information about a product via OCRs, the effectiveness of a firm's marketing efforts is adjusted. A more granular perspective on anchoring and adjustment is warranted as results of the IVEM, which suggests that consumers adjust their evaluations continuously and the influence of new sources is contingent on a dynamic interplay between various information inputs. Also, we are able to show the underlying mechanism as to why marketing efforts may become less influential for potential customers during the decision-making process. That is, the indirect effects of marketing efforts via confidence on purchase intention are mitigated as OCRs accrue, in that sufficient OCRs build confidence for prospective customers to make a trusted purchase decision. Hence, we uncover the trade-off process to which customers apply while using customer generated vs. firm provided information to make a purchase decision.

Additionally, our research provides several important extensions to the field's understanding of the role OCRs playing in consumer decision making. To date, the literature has traditionally focused on the isolated effects of OCRs on product performance, while in reality sources of information regarding the product jointly influence customers' decisions. More importantly, the limited research pertaining to the interactions between OCR and firm-initiated marketing efforts has predominantly considered and studied the static impact of those interactions. However, OCR and firm-initiated marketing efforts not only collectively influence customers' choices, but their relationships are dynamic and non-linear. Our research not only demonstrates the dynamic and non-linear relationships, but also extends the current scope of the literature by incorporating the tests of OCR's interacting relationships with the entire set of the four 4Ps marketing mix.

Furthermore, the marketing mix literature has shown that the effectiveness of companies' marketing efforts is not static and varies over time (Saboo, Kumar, and Park 2016). In some contexts, time has been leveraged as a convenient proxy for information availability. The empirical context for this study provides a unique context for us to actually measure the information availability as a product ages, thus allowing for modeling of the effects over our specific variable of interest rather than a proxy. Consequently, this research is the first of its kind to depict the effectiveness of companies' marketing efforts varying as a function of OCR information availability. Hence, we add a critical layer of granularity to comprehending the dynamic impacts of the marketing mix in the online shopping market. Such explicit examinations of how the effects of marketing mix variables vary over the volume of a specific variable of interest are important. And, consequently, a more pure test of the dynamic interplays between variables and more actionable insights into how to ideally manage marketing investments can be gleaned by their inclusion.

Managerial Implications

Our results suggest that there should be a shift in strategy for managing products launched and sold primarily through online channels. At the basic level, the results confirm the tremendous effect of OCRs by demonstrating both strong direct and moderating effects that impacted the effectiveness of companies' marketing efforts. Marketing managers should adopt a more proactive approach to drive OCR volume, more dynamically manage marketing efforts for online products, and calibrate product development and distribution based on the likelihood of receiving OCRs.

Encourage OCRs. Prior research has consistently demonstrated that OCRs have strong direct effects on sales, but the moderating effects of OCRs on companies' marketing efforts have received less consistent and even conflicting evidence in the literature (i.e., Chong et al. 2016; Lu et al. 2013). As a result, managers who likely understand the intuitive appeal of more online reviews are still left wondering, how many reviews are enough and should resources be focused more on generating OCRs or traditional marketing efforts. Our research provides the clearest insight into these questions, in that our research is the first to dynamically demonstrate the volume of OCRs that is required to enhance and/or detract from the effectiveness of a variety of marketing efforts (four Ps). Some volume of reviews is needed for certain marketing efforts to be effective (e.g., product variety and multichannel offering), and managers should actively encourage and even incentivize consumers to post online reviews. At the basic level, managers should encourage and embrace any type of reviews. However, to optimize effects, managers should encourage persuasive OCRs, as these OCRs are more efficient in updating the effects of companies marketing efforts, such as offsetting the positive impact of a price discount. Explicitly, managers can provide incentives for people who post informative reviews.

Pricing products dynamically. In addition to simply generating more OCRs, managers need to better monitor OCR volume and allocate discount offering budgets appropriately to get the best lift in sales performance. Specifically, the results reveal that discount works particularly well early in the lifecycle when no OCR exist or OCR volume is low. Once a sufficiently high number of OCRs are present (n = 49 in our data), price discounts become ineffective. Thus, discounts no longer drive sales at that time and should be greatly reduced in order to bolster profitability. As a simple example of the potentially lost profits due to inefficient discount expenditure, we conducted simple post-hoc calculations by selecting products with equal to or more than 49 OCRs. Then, we multiplied the discount amount and sales in units for each day after these products have 49 OCRs, which deems to be lost, suggesting an average total loss in revenue of $5,304 per product during the time period we collected our data. While this number might seem meager at first glance, firms in the fast fashion industry regularly launch over 10,000 new products/styles annually (Petro 2012), which translates to annual revenue losses of over $53 million.

Free shipping. Current competitive forces have required many firms to commit to free shipping policies in the short-term, but many executives are concerned that escalating shipping costs ($4.6 billion or 5 percent of total revenue in 2016 for Amazon.com according to the Sourcing Journal on December 5, 2016) might not be sustainable (Donaldson 2016). With rising costs, managers are under increased pressure to justify these shipping benefits. While prior work has shown that these shipping policies are significant drivers of sales (Koukova, Srivastava, and Steul-Fischer 2012; Lewis, Singh, and Fay 2006), our research uniquely demonstrates the non-linear and more calibrated effects of shipping while considering various levels of OCR volume in e-commerce. Although the effect of free shipping is dropped once OCRs are present, the impact is stable at a significant level over an entire range of OCRs, according to our Study 1. It would actually be safe to conclude that free shipping's influence is largely immune to OCR accumulation, and companies are better off providing free shipping the whole time to lift its profitability.

APPENDICES

APPENDIX A: TABLES

Table 2-1 Extant Studies of the Impact of OCRs on Product Sales

Citation	Dynamic Model	Marketing Mix				Jointly Model OCRs and Marketing	Process Examination[a]
		Price	Promotion	Product	Place		
This Research	Information Varying	✓	✓	✓	✓	✓	✓
Packard and Berger (2016)	✗	✗	✗	✗	✗	✗	✗
Neirotti, Raguseo, and Paolucci (2016)	✗	✗	✗	✗	✗	✓	✗
Minnema, Bijmolt, Gensler, and Wiesel (2016)	✗	✓	✗	✗	✗	✓	✗
Marchand, Hennig-Thurau, and Wiertz (2016)	Time Varying	✓	✓	✗	✗	✓	✗
Kostyra et al. (2016)	✗	✓	✗	✗	✗	✗	✗
Chong et al. (2016)	✗	✓	✓	✗	✗	✓	✗
Gopinath, Thomas, and Krishnamurthi (2014)	Time Varying	✗	✓	✗	✗	✓	✗
Zhao et al. (2013)	✗	✓	✗	✗	✗	✗	✗
Lu et al. (2013)	✗	✓	✗	✗	✗	✓	✗
Lingreen et al. (2013)	✗	✓	✗	✗	✗	✗	✗
Ho-Dac, Carson, and Moore (2013)	✗	✓	✗	✗	✗	✗	✗
Fang, Zhang, Bao, and Zhu (2013)	✗	✓	✗	✗	✗	✗	✗
Gu, Park, and Konana (2012)	✗	✓	✗	✗	✗	✗	✗
Cui, Lui, and Guo (2012)	✗	✓	✓	✗	✗	✗	✗
Bruce, Foutz, and Kolsarici (2012)	Time Varying	✗	✓	✗	✗	✓	✗
Ye, Law, Gu, and Chen (2011)	✗	✓	✗	✗	✗	✗	✗
Moe and Trusov (2011)	✗	✗	✗	✗	✗	✗	✗
Chen, Wang, and Xie (2011)	Time Varying	✓	✗	✗	✗	✗	✗
Archak, Ghose, and Ipeirotis (2011)	✗	✓	✗	✗	✗	✗	✗
Amblee and Bui (2011)	✗	✗	✗	✗	✗	✗	✗
Zhu and Zhang (2010)	✗	✓	✗	✗	✗	✗	✗
Zhang, Craciun, and Shin (2010)	✗	✗	✗	✗	✗	✗	✗
Yang and Mai (2010)	✗	✓	✗	✗	✗	✗	✗
Moon, Bergey, and Iacobucci (2010)	Time Varying	✓	✓	✗	✗	✓	✗
Chintagunta, Gopinath, and Venkararaman (2010)	✗	✗	✗	✗	✗	✗	✗
Dhar and Chang (2009)	✗	✗	✗	✗	✗	✗	✗
Li and Hitt (2008)	✗	✓	✗	✗	✗	✓	✗
Hu, Liu, and Zhang (2008)	✗	✓	✗	✗	✗	✗	✗
Forman, Ghose, and Wiesenfeld (2008)	✗	✓	✗	✗	✗	✗	✗
Duan, Gu, and Whinston (2008)	✗	✗	✗	✗	✗	✗	✗
Liu (2006)	✗	✗	✗	✗	✗	✗	✗
Clemons Gao, and Hitt (2006)	✗	✗	✗	✗	✗	✗	✗
Chevalier and Mayzlin (2006)	✗	✓	✗	✗	✗	✗	✗
Godes and Mayzlin (2004)	✗	✗	✗	✗	✗	✗	✗

a:Mediation test that uncovers how OCR volume moderates effects of marketing mix.

Table 2-2 Study 1: Variable Description

Purpose in Study	Variables	Operationalization
Dependent variables	Sales ($\ln(S_{ij})$)	Log of daily sales (in unit) +1 for product i at time j.
Independent variables	Discount ($disount_{ij}$)	Ratio of discount amount to original price for product i at time j.
	Free shipping (fs_{ij})	Whether product i at time j offers free shipping. Assign 1 to free shipping and 0 to no free shipping
	Product variety ($pro\_variety_i$)	Log of multiplication of the number of colors and the number of sizes that product i provides to customers
	Multichannel ($multichannel_i$)	Whether product i is available both online and offline. Assign 1 to both online and offline and 0 to online only
Moderators	Volume (v_{ij})	Cumulative number of OCRs for product i at time j.
	Inform_volume ($v_{ij}^{informative}$)	Cumulative number of informative OCRs for product i at time j. Informative OCRs are those at least containing information about one category out of the seven categories that are identified by the two researchers when coding reviews.
Covariates	Valence ($valence_{ij}$)	Cumulative average rating of available OCRs for product i at time j
	Variance ($variance_{ij}$)	Cumulative variance of ratings of available OCRs for product i at time j
	L_totalsales ($l\_totalnit_{ij}$)	Cumulative total sales (in unit) of product i at time j
	Price (org_price_i)	Log of original price of product i
	Maturity ($maturity_{ij}$)	Number of days that product i has been on market at time j
	Holiday ($holiday_{ij}$)	Whether it is a holiday for product i at time j. Assign 1 to holidays and 0 to non-holidays. The holidays include Father's day, Bestie's day, Groupon sales day, and Semiannual sales day
	Weekend ($weekend_{ij}$)	Whether it is a weekend (Saturday or Sunday) for product i at time j. Assign 1 to weekends and 0 to weekdays
	Brand dummies ($Brand_1$ to $Brand_{11}$)	A series of brand dummy variables with $Brand_{12}$ as the reference group

Table 2-3 Study 1: Summary Statistics and Correlation Matrix of Pre-OCR Dataset

Pre-OCR	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**
1.Sales	0.981	1.076	1				
2.Discount	0.228	0.276	0.121**	1			
3.Product variety	1.666	0.421	0.009**	0.112**	1		
4.L_totalsales	16.848	32.391	0.258**	0.022	-0.032	1	
5.Price	5.904	0.506	-0.184**	0.091**	0.161**	-0.072**	1
6.Maturity	11.39	12.150	-0.234**	0.015	0.158**	0.050*	0.145**
	Frequency						
Free shipping	1: 0.217; 0: 0.783						
Multichannel	1: 0.837; 0: 0.163						
Holiday	1: 0.797; 0: 0.203						
Weekend	1: 0.260; 0: 0.740						

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
n=2,492

Table 2-4 Study 1: Summary Statistics and Correlation Matrix of Post-OCR Dataset

Post-OCR	Mean	SD	1	2	3	4	5	6	7	8	9
1.Sales	0.826	1.036	1								
2.Discount	0.392	0.332	0.030**	1							
3.Product variety	1.672	0.417	0.104**	0.167**	1						
4.Volume	19.116	24.068	0.152**	-0.079**	0.063**	1					
5.L_totalsales	68.371	99.469	0.212**	-0.032**	0.134**	0.462**	1				
6.Price	5.720	0.544	-0.058**	0.220**	0.074**	-0.266**	-0.161**	1			
7.Maturity	53.261	26.518	-0.028**	0.057**	0.014*	0.325**	-0.213**	0.052**	1		
8.Valence	4.820	0.174	0.015*	-0.013	0.010	-0.005	0.024**	-0.130**	-0.084**	1	
9.Variance	2.487	1.712	-0.002	0.092**	0.033**	0.099**	0.017*	0.084**	0.234**	-0.278**	1
10.Inform_volume	13.987	18.136	0.146**	-0.088**	0.040**	0.989**	0.461**	-0.255**	0.311**	-0.016*	0.110**
	Frequency										
Free shipping	1: 0.248; 0: 0.752										
Multichannel	1: 0.594; 0: 0.406										
Holiday	1: 0.233; 0: 0.767										
Weekend	1: 0.294; 0: 0.706										

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
n=21,340

Table 2-5 Study 1: First-Stage Results for Endogenous Variables

Variable	Coefficient Estimate	SE
Discount (n = 23,832)		
Δ ln(S_{ij-1})	-0.004***	0.001
Δ ln(S_{ij-2})	-0.004***	0.001
Δ $discount_{ij-1}$	0.418***	0.012
Δ $discount_{ij-2}$	0.334***	0.020
Constant	0.380***	0.016
R Square	10.00%	
Free Shipping (n = 23,832)		
Δ ln(S_{ij-1})	0.055***	0.007
Δ ln(S_{ij-2})	0.001	0.006
Δ fs_{ij-1}	2.307***	0.088
Δ fs_{ij-2}	1.216***	0.080
Constant	-0.798***	0.061
Pseudo R Square	16.76%	
OCR Volume (n = 23,832)		
High temperature_north	0.023***	0.006
High temperature_south	0.687***	0.079
High temperature_west	-0.252***	0.038
High temperature_east	0.746***	0.071
High temperature_northeast	0.381***	0.028
High temperature_southwest	-0.171***	0.017
High temperature_central	0.260***	0.023
Wind_north	-0.624***	0.053
Wind _south	-0.157***	0.025
Wind _west	-0.797***	0.079
Wind _east	-2.242***	0.152
Wind _northeast	-0.660***	0.059
Wind _southwest	0.190***	0.042
Wind _central	-0.181*	0.090
Sunny_north	-4.125***	0.321
Sunny _south	0.896***	0.240
Sunny _west	0.529*	0.263
Sunny _east	-4.743***	0.337
Sunny_northeast	-2.707***	0.222
Sunny_southwest	-0.374*	0.163
Sunny_central	0.374*	0.161
Cloudy_north	-1.393***	0.150
Cloudy_south	-0.911***	0.131
Cloudy_west	-1.715***	0.166
Cloudy_east	-2.906***	0.208
Cloudy_northeast	-1.303***	0.116
Cloudy_southwest	-1.613***	0.156
Cloudy_central	-0.142*	0.065
Constant	30.708***	1.937
R Square	34.21%	

*: p-value < .05; **: p-value < .01; ***: p-value < .001

Table 2-6 Study 1: Results of Baseline Models

Variable	Pre-OCR Model		Post-OCR Model	
	Coefficient	SE	Coefficient	SE
Discount	0.562***	0.257	0.307***	0.076
Free shipping	1.027***	0.088	0.721***	0.035
Product variety	0.032	0.098	0.121**	0.043
Multichannel	0.022	0.176	0.087	0.062
Valence	NA	NA	0.035	0.054
Variance	NA	NA	-0.007	0.006
L_totalsales	0.007***	0.001	0.001***	0.000
Price	-0.286*	0.110	-0.122**	0.043
Holiday	-0.071	0.070	0.216***	0.024
Weekend	0.082*	0.039	0.049***	0.015
Maturity	-0.001	0.002	0.003***	0.000
Brand_1	0.310	0.308	-0.062	0.096
Brand_2	-0.764	0.502	-0.228	0.234
Brand_3	-0.063	0.289	0.098	0.081
Brand_4	0.124	0.216	0.322***	0.085
Brand_5	-0.056	0.225	0.144	0.082
Brand_6	-0.503	0.288	-0.182	0.097
Brand_7	-0.692*	0.280	-0.123	0.099
Brand_8	-0.026	0.290	0.276***	0.072
Brand_9	0.059	0.364	0.082	0.165
Brand_10	-0.382	0.232	-0.099	0.101
Brand_11	-0.301	0.190	-0.096	0.071
$\widehat{\eta_{ij}^{discount}}$	0.147[a]	0.268	-0.317***	0.084
$\widehat{\delta_{ij}^{fs}}$	-0.323***	0.060	-0.202***	0.024

*. p<.05; **. p<.01; ***. p<.001

Sample size: Pre-OCR n=2,492; Post-OCR n=21,340

a: the insignificant residual indicates that discount is not endogenous during the pre-OCR period. This may be due to the fact that managers have limited historical records on sales and discount of a certain product to determine the future discount and the actual discount decision during this period is more random.

Table 2-7 Study 1: Model Comparison

Model	-2 Res Log Likelihood	AIC
Base model	59,383.4	59,387.4
Monotonic model	59,301.9	59,305.9
IVEM	59,180.0	59,274.0

Table 2-8 Study 2: Results of Moderated Mediation Testing

	Coefficient	Confidence Interval
Main and Interaction Effects		
Price Discounts → Confidence	1.41*	[0.86, 1.96]
OCR Volume → Confidence	2.27*	[1.81, 1.96]
Price Discount x OCR Volume → Confidence	-1.03*	[-1.70, -0.36]
Price Discount → Purchase Intent	0.47*	[0.26, 0.68]
Confidence → Purchase Intent	0.85*	[0.79, 0.92]
Conditional Indirect Effects		
No OCR Volume: Price Discount → Confidence → Purchase Intent	1.21*	[0.64, 1.69]
OCR Volume: Price Discount → Confidence → Purchase Intent	0.32*	[0.06, 0.63]
Moderated Mediation		
Index of Moderated Mediation	-0.88*	[-1.51, -0.26]

Notes: Confidence intervals are 95% bias-corrected intervals based on 10,000 bootstrapped samples.
* $p < .05$

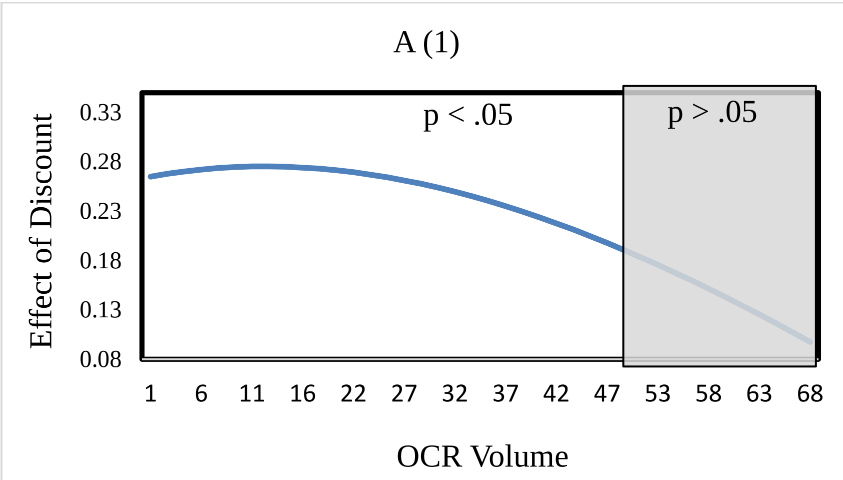
Table 2-APPENDIX Study 1: Endogeneity Correction

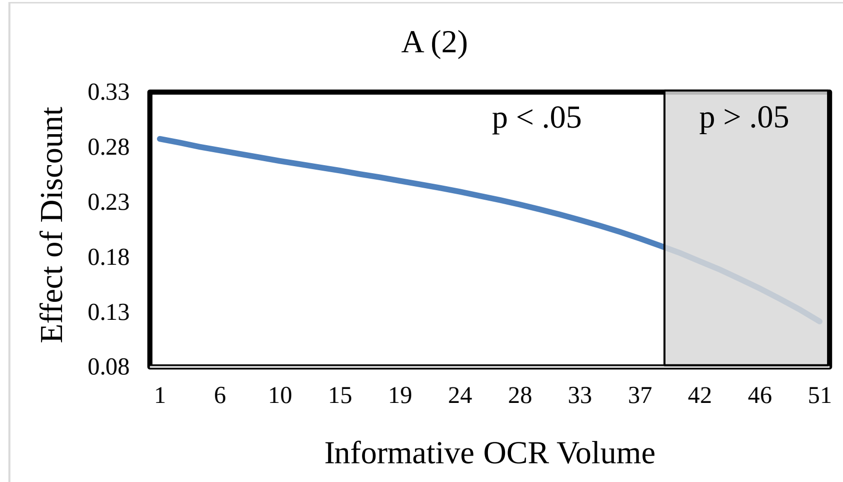
Variables	**Pre-OCR Model**				**Post-OCR Model**			
	w/o control functions		**with control functions**		**w/o control functions**		**with control functions**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Discount	0.942***	0.127	0.562***	0.257	0.019	0.032	0.307***	0.076
Free shipping	0.736***	0.044	1.027***	0.088	0.467***	0.019	0.721***	0.035
Product variety	0.134	0.114	0.032	0.098	0.131**	0.044	0.121**	0.043
Multichannel	-0.158	0.206	0.022	0.176	0.051	0.064	0.087	0.062
Valence	NA	NA	NA	NA	0.035	0.054	0.035	0.054
Variance	NA	NA	NA	NA	-0.011	0.006	-0.007	0.006
Lag_totalsles	-0.004***	0.001	0.007***	0.001	0.001***	0.000	0.001***	0.000
Price	-0.456**	0.147	-0.286*	0.110	-0.114**	0.044	-0.122**	0.043
Holiday	-0.181***	0.047	-0.071	0.070	0.180***	0.024	0.216***	0.024
Weekend	0.015	0.035	0.082*	0.039	0.032*	0.015	0.049***	0.015
Maturity	0.001	0.002	-0.001	0.002	0.002***	0.000	0.003***	0.000
Brand_1	-0.519	0.317	0.310	0.308	-0.043	0.096	-0.062	0.096
Brand_2	-1.562*	0.736	-0.764	0.502	-0.041	0.240	-0.228	0.234
Brand_3	-0.026	0.272	-0.063	0.289	0.162	0.083	0.098	0.081
Brand_4	0.029	0.278	0.124	0.216	0.344***	0.088	0.322***	0.085
Brand_5	-0.259	0.271	-0.056	0.225	0.264**	0.082	0.144	0.082
Brand_6	-0.645*	0.304	-0.503	0.288	0.007	0.087	-0.182	0.097
Brand_7	-0.970**	0.308	-0.692*	0.280	0.073	0.089	-0.123	0.099
Brand_8	1.473***	0.252	-0.026	0.290	0.282***	0.075	0.276***	0.072
Brand_9	-0.360**	0.530	0.059	0.364	0.092	0.171	0.082	0.165
Brand_10	-0.834***	0.318	-0.382	0.232	-0.035	0.104	-0.099	0.101
Brand_11	-0.773	0.227	-0.301	0.190	-0.038	0.073	-0.096	0.071
$\eta_{ij}^{\widehat{discount}}$			0.147	0.268			-0.317***	0.084
$\widehat{\delta_{ij}^{fs}}$			-0.323***	0.060			-0.202***	0.024
-2 Res Log Likelihood	6010.8		4218.7		59763.6		59383.4	
AIC	6014.8		4222.7		59767.6		59387.4	
Sample size	2,492		2,492		21,340		21,340	

*: p-value < .05; **: p-value < .01; ***: p-value < .001

APPENDIX B: FIGURES

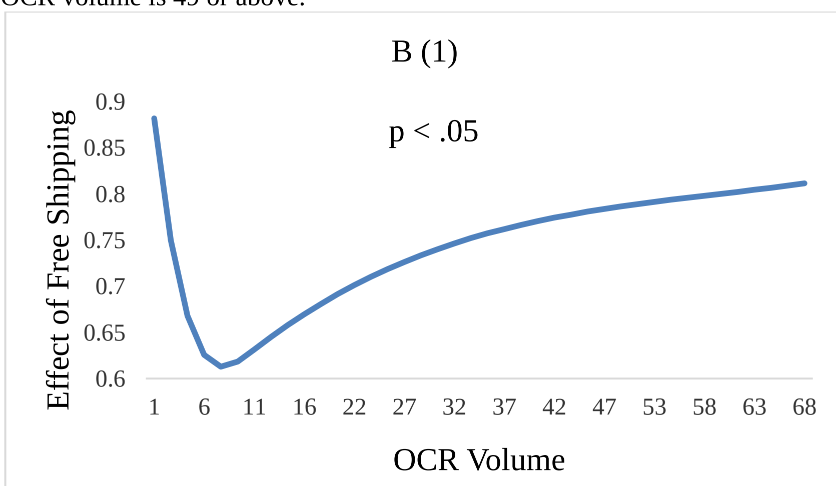
Figure 2-1 Study 1: Effects of Discount and Free Shipping Across OCR Ranges

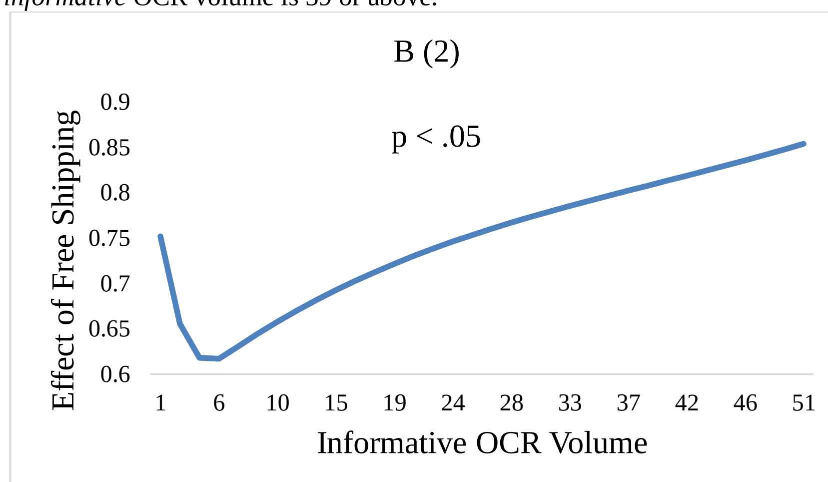




Interpretation: The positive effect of discount becomes insignificant when OCR volume is 49 or above.

Interpretation: The positive effect of discount becomes insignificant when *informative* OCR volume is 39 or above.

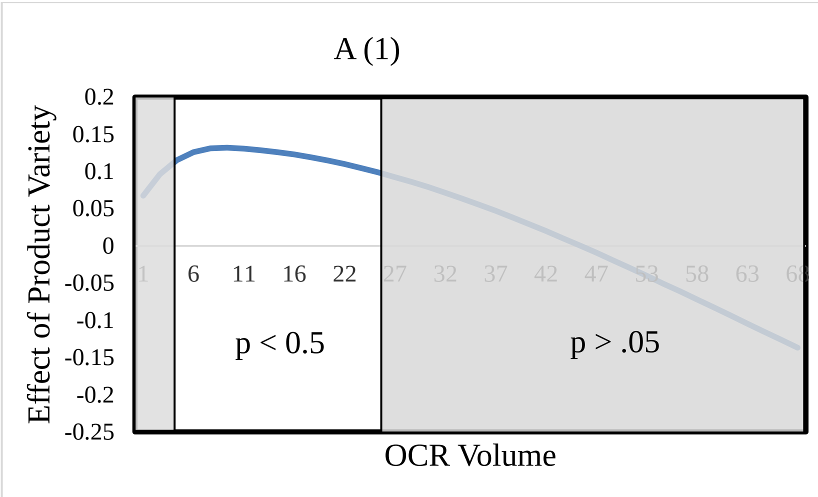




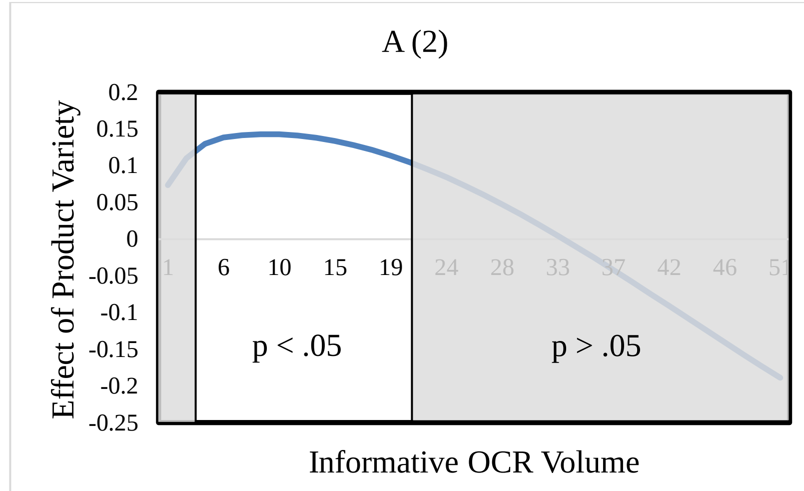
Interpretation: The positive effect of free shipping decreases and then maintains at a lower but significant level.

Interpretation: The positive effect of free shipping decreases and then maintains at a lower but significant level.

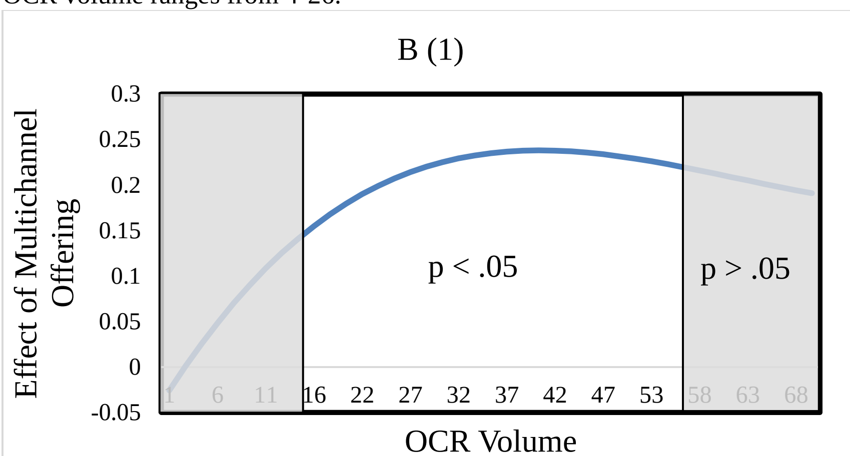
Figure 2-2 Study 1: Effects of Product Variety and Multichannel Offering Across OCR Ranges



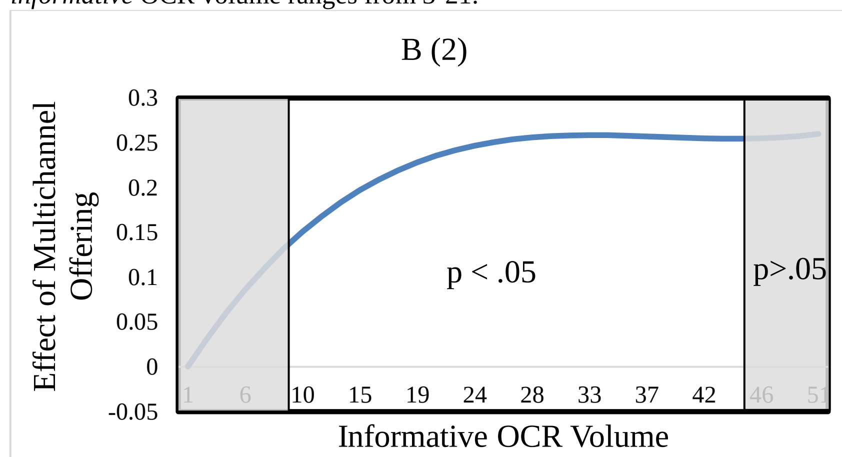
Interpretation: The positive effect of product variety is only significant when OCR volume ranges from 4-26.



Interpretation: The positive effect of product variety is only significant when *informative* OCR volume ranges from 3-21.

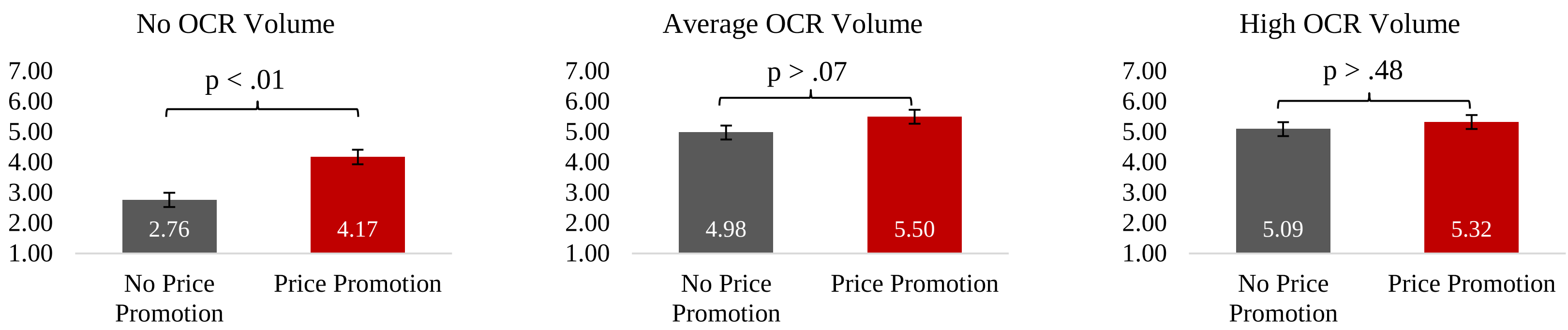


Interpretation: The positive effect of multichannel offering is only significant when OCR volume ranges from 15-55.



Interpretation: The positive effect of multichannel offering is only significant when *informative* OCR volume ranges from 9-45.

Figure 2-3 Study 2: Mean Differences in Customer Confidence Across Varying Levels of Price Discount and OCR Volume



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CONCLUSION OF DISSERTATION

As a marketing strategy scholar, the primary mission of my dissertation is to deliver strategic levers to managers to enhance their e-commerce business performance and cope better with the challenges they face daily. In other words, my dissertation provides managerial implications to change managers' behavior to achieve better outcomes. Specifically, the offerings advanced by this dissertation include changing the views of managers on return instances and on dynamic allocations of marketing budgets by incorporating online reviews. More importantly, within the research scope of e-commerce, this dissertation endeavors to enrich the literature on product returns (essay one) as well as the literature on OCR and marketing mix (essay two). Below, I will concisely summarize the theoretical and managerial contributions of my dissertation.

Theoretical contributions: Essay one uses two empirical studies via two samples from various companies to comprehend product returns in e-commerce in terms of their antecedents and consequences. As strategically important as product returns are to firms, especially their e-commerce units, scant research has been conducted to shed light on remedies to manage return rates (e.g., Petersen and Kumar 2009). The limited insights in this regard are not efficient; neither do they confront the fundamental cause of return instances. I show theoretically and empirically that traditional and mobile online channels are different in terms of providing customer information search experiences (i.e., gathering information and reviewing alternatives, Aksoy et al. 2013; Joy et al. 2009; Wang, Malthouse, and Krishnamurthi 2015), thus leading to various return rates and also adjusting marketing information's impacts on return rates as well. Given these dual roles of channels, I argue that channel coordination in online contexts is a remedy for managers to reduce return rates in e-commerce. Specifically, mobile channel usage can reduce return rates and especially help reduce returns of highly promoted products, due to the larger consideration set built on mobile channels. Yet, traditional online channels are particularly efficient in reducing the return rates of expensive products. These proposed strategies are manageable and economically efficient for firms, and they offer what customers need in the purchasing process to avoid returns.

Additionally, dominant claims on the economic costs of returns and recent arguments on the positive impacts of returns on future purchases call for further research to comprehensively evaluate the consequences of returns. This research responds to the above request and articulates that returns can be both good and bad, depending on product categories that are returned by customers. For some product categories, where it is hard to leverage prior return experiences, customers perceive returns as failures, feel hesitant to purchase 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; thus, they will purchase more in their next order. This research introduces the first contingent variable to the understanding of returns' consequences and reconciles the conflicting arguments in the return literature regarding its after-effects.

Essay two also employs two studies via various research methods to depict the true relationships between OCRs and marketing efforts using IVEM, and uncover why the impacts of marketing efforts vary over levels of OCRs using a lab experiment. This research is the first of its kind to propose and empirically demonstrate the dynamic and non-linear relationships between OCRs and marketing efforts and indicate that the relationships are far more complicated than prior research suggests. With the aid of lab experiments, essay two uncovers the trade-off process to which customers apply while using customer-generated vs. firm-provided information to make a purchase decision. Specifically, it shows that the indirect effects of marketing efforts via confidence on purchase intention are mitigated as OCRs accrue, in that sufficient OCRs build confidence for prospective customers to make a trusted purchase decision. Furthermore, the marketing mix literature has shown that the effectiveness of companies' marketing efforts is not static and varies over time (Saboo, Kumar, and Park 2016). In some contexts, time has been leveraged as a convenient proxy for information availability. This research provides a unique context to actually measure information availability as a product ages, thus allowing for modeling the effects over the specific variable of interest rather than a proxy. Hence, I add a critical layer of granularity to comprehending the dynamic impacts of the marketing mix in the online shopping market.

Managerial contributions: Essay one tackles product return issues in e-commerce. It indicates that channel coordination (coordinating mobile channels and traditional online channels) is a strategic remedy to manage returns effectively. Given the unique features of these two channels, essay one suggests that instead of selecting one channel over the other, firms need to synchronize the two sub-channels in e-commerce to maximize their effectiveness in managing returns. For instance, firms should entice those customers with high return rates to use mobile channels to reduce their return rates, by launching exclusive mobile promotion events and/or sending mobile notifications to those customers. Also, firms can display heavily promoted products on mobile channels exclusively to decrease their return rates. In the meantime, they should present expensive product categories on traditional online channels. In addition, learning from mobile channels, traditional online channels are better off in helping customers conduct larger consideration sets while shopping, such as adjusting the design of traditional online channels by facilitating the searching process for customers. Lastly, although returned products generate all kinds of cost for firms, we suggest that return instances can bring entirely different outcomes to firms in terms of customers' future purchases. We advise that firms ought to evaluate the nature of their customer returns before they take action on implementing strategies to manage them. 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. 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 use their return experiences in future shopping.

Broadly, essay two depicts the dynamic and non-linear relationships between OCRs and the entire set of four Ps marketing tactics. Since some volume of reviews is needed for certain marketing efforts to be effective (e.g., product variety and multichannel offering), managers should actively encourage and even incentivize consumers to post online reviews. To optimize effects, managers should encourage persuasive OCRs (i.e., informative reviews), as these OCRs are more efficient in updating the effects of companies' marketing efforts, such as offsetting the positive impact of a price discount. More so, managers need to better monitor OCR volume and allocate discount offering budgets appropriately to get the best lift in profits. Analyzing their own data, firms can find the sweet spot to stop offering discounts to customers while maintaining the same level of sales. More intriguingly, this research finds that free shipping's influence is largely immune to OCR accumulation, and companies are better off providing free shipping the whole time to lift its profitability.