HARVARD | BUSINESS | SCHOOL

Opportunistic Returns and Dynamic Pricing: Empirical Evidence from Online Retailing in Emerging Markets

Chaitanya Bandi
Donald Ngwe
Antonio Moreno
Zhiji Xu

Working Paper 19-030

Opportunistic Returns and Dynamic Pricing: Empirical Evidence from Online Retailing in Emerging Markets

Chaitanya Bandi
Northwestern University

Antonio Moreno
Harvard Business School

Donald Ngwe
Harvard Business School

Zhiji Xu
Northwestern University

Working Paper 19-030

Opportunistic Returns and Dynamic Pricing: Empirical Evidence from Online Retailing in Emerging Markets

Chaitanya Bandi[1], Antonio Moreno[2], Donald Ngwe[3], and Zhiji Xu[1]

[1] *Operations Department, Kellogg School of Management, Northwestern University, Evanston, IL 60208*

[2] *Technology and Operations Management Unit, Harvard Business School, Boston, MA 02163*

[3] *Marketing Unit, Harvard Business School, Boston, MA 02163*

September 2018

Abstract

We investigate how dynamic pricing can lead to more product returns in the online retail industry. Using detailed sales data of more than two million transactions from the Indian online retail market, where price promotions are very common, we document two types of strategic customer behavior that have not been considered in previous research. First, customers who monitor product prices after purchase may initiate *opportunistic returns* because of price drops. Second, customers who anticipate a future return may *strategically choose a payment method* that facilitates product returns. Our logistic regression models indicate that (1) realized post-purchase price drops lead to a higher probability of return, and (2) anticipated price drops after purchase lead to a higher probability of using *cash on delivery*, a payment method with a lower return cost for consumers. Our findings are robust to alternative model specifications and sample selection procedures. We demonstrate that an optimal pricing policy should take into consideration the potential costs of two types of strategic customer behavior: opportunistic returns and strategic choice of payment method.

Keywords: cash on delivery; dynamic pricing; emerging markets; online retail; opportunistic returns; payment methods; strategic customer behavior

INTRODUCTION

Dynamic pricing has been widely applied in various industries, such as airline ticketing, ride-sharing, and online retailing. It has been widely established that, when appropriately applied, dynamic pricing can substantially increase profits for the firm (e.g. Sahay 2007). In the face of dynamic pricing, customers may choose to delay purchases in expectation of future discounts. This strategic waiting behavior complicates the design of optimal dynamic pricing policies (e.g. Nair 2007; Su 2007), because the firm is effectively competing with itself over several time periods (the Coase conjecture, see Coase 1972). Recent studies have further explored the interaction between strategic waiting behavior and dynamic pricing (e.g. Swinney 2011; Li et al. 2014).

In this paper, we use transaction data from the Indian online retail market to document two dimensions of strategic customer behavior that have not been considered in previous research. First, in the online retail industry, price drops can induce product returns by customers who monitor product prices after purchase. We call this type of strategic behavior *opportunistic returns*, because customers are opportunistically seeking benefits from price changes. Second, when there is more than one payment method available, customers who anticipate a future price drop after purchase may choose a payment method with a lower return cost. We call this strategic behavior *strategic choice of payment method*. Both types of strategic behavior arise from dynamic pricing, and both can have significant profit implications.

Opportunistic returns are important because returns play a critical role in customer satisfaction and supply chain management for online retailers. Returns can hurt retailers by posing substantial costs in shipping, handling, and liquidation (Ng and Stevens 2015; Tang 2016). Reducing returns is a key objective for any retailer, especially for online retailers, as up to one-third of all Internet transactions are returned by customers (Banjo 2013). Past research has shown that fit uncertainty is one cause of product returns (Anderson et al. 2009; Gallino and Moreno 2017). In this paper, we identify a novel factor that can result in product returns from customers: observed post-purchase price drops. These price-related returns, or what we term *opportunistic returns*, impose additional costs on the online retailer.

Strategic choice of payment method is important in our context of emerging markets, because the payment method we study, cash on delivery (COD), is widely used. COD is a payment method in which customers pay for products at the time of receipt. This payment method has long been applied in traditional retail, and remains widely used in e-commerce sectors in emerging markets, including China, Russia, and India, where many customers do not have credit cards. In particular, COD accounts for up to 60 percent of online transactions in India (Nair 2013), from where our data originated. One feature of COD is that customers can decline the delivery at the door without paying anything, which effectively reduces the return cost perceived by customers at the time of purchase. Taking this into consideration, we hypothesize that customers who expect a higher probability of returning the product would choose to purchase by COD more frequently. We say these customers *strategically* choose the payment method, and we find empirical evidence from the data that confirms this strategic behavior. Moreover, there is anecdotal evidence that COD purchases are associated with higher return rates (Das 2014). We are able to verify this proposition using our data, and we argue that the reasons for high return rates include not only the lower cost of returns, but also the strategic choice of payment method.

We have partnered with one of the leading online apparel retailers in India, and gained access to a detailed sales data set of over two million transactions with return and method of payment information. Our unique data set, together with our econometric approach, allows us to make two main contributions.

First, our paper is the first, to our knowledge, to provide empirical evidence that dynamic pricing can lead to an increase in product returns. We demonstrate that there are strategic customers who monitor price trajectories and strategically return their purchased products if they observe a price drop after their purchase. These opportunistic returns can translate to substantially higher return volumes when the total number of transactions is in the millions, translating into a substantial increase in additional costs.

Second, we establish a link between dynamic pricing and the use of the COD payment method. We find that COD can be used strategically by customers who think they are likely to return a purchase. Specifically, if customers believe that prices will probably drop after their purchase, they are more likely to use COD. We show that there is a positive and statistically significant effect of perceived probability of price drops on the likelihood of using COD. To the best of our knowledge, our paper is the first to study the strategic use of payment method in the face of dynamic pricing.

The remainder of the paper is organized as follows. We introduce background information on e-commerce in India and cash on delivery and summarize relevant prior research. Next, we develop our main hypotheses and discuss the institutional setting and the data. Then we describe our econometric approach and report empirical results related to our hypotheses. Finally, we conclude the paper and identify areas for future research.

BACKGROUND AND RELATED LITERATURE

E-Commerce in Emerging Markets

E-commerce has been growing rapidly in emerging markets. According to the Emerging Consumer Survey (Credit Suisse 2016), the size of the online retail industry in nine developing countries, including China, India, and Brazil, could increase from a current annual turnover of USD 731 billion to USD 2.5 trillion by 2025, which would represent a 13 percent annual growth rate. The main driver of this growth is the increasing level of Internet access for consumers in emerging markets, especially for lower-income groups. In addition, the rise in smartphone usage in emerging markets also plays an important role.

E-commerce adoption in India has historically lagged behind other major emerging markets, but has recently been growing at an unprecedented rate. The size of the e-commerce market grew from USD 2.9 billion in 2013 to USD 16.0 billion in 2015 (Confederation of Indian Industry 2016). Online retailing is the fastest-growing segment, having grown at an average annual rate of around 56 percent (PwC India 2015). Flipkart, considered the biggest e-commerce venture in

India, started with USD 10 million GMV (General Merchandise Value) in 2007, and achieved USD 1 billion GMV in 2014 and USD 4 billion GMV in 2015 (Sharmal 2016). Snapdeal, another major Indian e-commerce company, grew by roughly 500 percent between 2012 and 2013, and achieved USD 2.2 billion GMV in May 2015 (Singh 2016).

One unique feature of e-commerce in India is the high frequency of festive season sale events. These festive seasons often coincide with religious holidays and festivals, of which there are several in the country. Most festivals are concentrated from September to December. For example, up to 40 percent of the country's annual online spending can be generated during the Diwali discount period (Rai 2015). E-commerce companies invariably make use of the occurrence of festivals and launch frequent festive season sale events. As a result, there are high levels of price fluctuations during these periods (Punit 2015; Dalal 2016). This makes the Indian market particularly suitable for examining the effects of dynamic pricing.

Another feature of e-commerce that is prominent not only in India but also in many other emerging markets is the popularity of cash on delivery (COD). COD is a payment method where customers pay for products at the time of receipt. COD is popular for the following three reasons. First, the penetration of online payment methods such as credit cards and debit cards is relatively low. Although credit cards have the benefit of delaying payment if funds are not immediately available at the moment of purchase, consumers in emerging markets often retain a preference for cash transactions over credit card transactions. Specifically, according to India's central bank, the country, with a population of more than 1.3 billion, had only 24.51 million credit cards in use in March 2016 (RBI 2016). Second, even if a customer owns a credit card, he or she may be reluctant to use it when buying online because of inconvenience and security concerns. According to the Emerging Consumer Survey (Credit Suisse 2016), only 43 percent of the respondents' spending was done using a credit card. Third, when buying from a new online retailer, customers may trust the merchant less than if they could first inspect the physical product. According to the same survey, online customers in emerging markets care most about a site's trustworthiness when deciding where to buy online. As a result, almost all e-commerce companies offer the cash on delivery option, and COD accounts for up to 60 percent of online transactions in India, according to a study by the Internet and Mobile Association of India and KPMG, a major auditing firm (Nair 2013).

While COD facilitates consumer adoption of e-commerce, there are substantial costs associated with this payment method for merchants. First, COD transactions often require partnership with delivery companies, longer collection cycles, and higher instances of mishandling and theft. In a typical COD transaction for our data provider, a customer pays cash to the delivery person, who transfers the funds to his or her supervisor, who then remits the funds to the e-commerce company. The time it takes for the company to receive the cash is typically 3 to 5 days, depending on the delivery area. In extreme cases, the settlement period can last as long as three weeks. Second, we show that COD purchases have a higher probability of return, as buyers are less committed to the purchase than if they had paid in advance. In most cases, customers can decline delivery at the door for free, requiring the delivery person to return the product to the company. Returns can hurt the company not only through higher logistics costs due to round-trip transportation, but also through the inventory costs of potential reordering from upstream firms in the supply chain. Both of these costs can be amplified as transit time increases, particularly given India's vast territory and existing infrastructure. One Indian e-commerce company has estimated that cash on delivery transactions add about 3 percent in additional costs, and the costs can go up by as much as 30 percent with returns (Nair 2013).

Although research has been performed on other popular financial products in emerging economies such as mobile money (the use of electronic money transfers through cellular networks, see Balasubramanian and Drake 2015), supplier finance (see Tunca and Zhu 2017), and information technology (see Parker et al. 2016), the choice of payment method has not been investigated in depth in the literature. In particular, COD, a very popular payment method in emerging economies, has not been studied. Our paper is the first to provide an analysis of the cause and consequences of payment-method choices.

Fulfillment and Returns in Online Retail

There is a growing body of academic literature studying fulfillment and returns in e-commerce. Anderson et al. (2009) provided an analysis of the option value of returns for consumers using a structural modeling framework. Several papers have focused on consumer returns due to poor match in taste and fit (e.g. Anderson et al. 2009; Altug and Aydinliyim 2016; Gallino and Moreno 2017). Ofek et al. (2011) showed how customer returns influence multichannel firms' decisions in determining prices and setting service levels in offline channels. Previous work has also illustrated how free return policies can have large, positive effects on customer satisfaction and lifetime value (Petersen and Kumar 2009; Bower and Maxham 2012), whereas other work has examined the feasibility of charging customers for returns in competitive settings (Wood 2001; Shulman et al. 2011). In this paper, we provide empirical evidence of return behaviors that arise due to a previously unexamined but commonly observed factor, dynamic pricing, and argue that such price-related returns can affect decisions for both firms and customers.

Product returns and online fulfillment have also been a focus of research in operations management (Agatz et al. 2008). Randall et al. (2006) studied the optimal inventory and fulfillment choices in the context of online retailers and tested their results empirically with data. Rao et al. (2011) linked online fulfillment with the future purchase behavior of customers. These studies focused directionally on fulfillment from retailer to customer (B2C), but not on the other direction: consumer returns. Recently, fulfillment has been studied in an omni-channel environment, where customers shop online and offline at the same retailer. For example, Bell et al. (2017) studied the impact of offline showrooms on demand, conversions, and product returns.

Operations management research on consumer returns has been directed primarily to supply chain performance and optimal design (e.g. Guide et al. 2006; Su 2009; Shulman et al. 2009). Product returns can also be thought of as human factors in supply chain management, which relate to inventory inaccuracy (e.g. DeHoratius and Raman 2008; DeHoratius et al. 2008).

Dynamic Pricing and Strategic Customer Behavior

The benefits of dynamic pricing have been widely acknowledged and documented in a vast literature, particularly with respect to online retail settings (Kannan and Kopalle 2001). It has been shown that, from a company's perspective, appropriately applied dynamic pricing policies can increase revenue and profits (Sahay 2007). In response to dynamic pricing, strategic consumers who expect a future discount may find a current purchase less attractive. As a result, a naïve dynamic pricing strategy that ignores strategic customer behavior can prove to be suboptimal. The interaction between dynamic pricing and customers' strategic waiting behavior has been studied extensively in the theoretical literature (e.g. Aviv and Pazgal 2008; Cachon and Swinney 2009; Swinney 2011; Papanastasiou and Savva 2014). These studies extend the seminal work by Besanko and Winston (1990), which studies a game between a monopolist setting prices for a new product over time and strategic consumers deciding whether to purchase now for guaranteed utility or postpone the purchase so as to maximize future expected utility. These papers characterize different equilibria in which the monopolist generally reduces prices over time. Further research has explored how dynamic pricing interacts with consumer risk aversion (Liu and Van Ryzin, 2008), regret (Nasiry and Popescu, 2012), and price search (Yuan and Han, 2011).

Previous studies have explored the interaction between dynamic pricing and strategic consumer behavior in specific empirical settings. Nair (2007) investigated the optimal intertemporal pricing policy given strategic customers in the video game industry. Li et al. (2014) applied a structural estimation model to show the existence of strategic customer behavior in the airline industry. Soysal and Krishnamurthi (2012) studied demand dynamics in the seasonal goods industry. Our focus is on the online retail industry, in which the fulfillment of purchased products comes into consideration and strategic customer behavior can arise in the forms of opportunistic returns or payment-method choices. To the best of our knowledge, this paper is the first to document and analyze these behaviors.

HYPOTHESIS DEVELOPMENT

In order to motivate our research hypotheses, we begin by discussing possible reasons why customers return products in the online retail industry. Customers choose to return a purchased product if and only if the benefit of returning outweighs the cost. The cost of returning a product includes postal, transportation, and hassle costs. In the following discussion, we give examples of potential factors that affect the benefit of returns.

One reason for returning a product is that customers may gain additional information on fit by trying on the product. In other words, returns occur after the resolution of fit uncertainty. Previous studies about product returns mainly focused on fit-related returns (e.g. Anderson et al. 2009; Su 2009; Gallino and Moreno 2017). In terms of the ex ante benefit of a lenient return policy, the benefit of returns is positively associated with fit uncertainty: the larger the fit uncertainty, the larger the benefit of returns.

On the other hand, strategic customers who monitor product price trajectories may return the purchased product if they observe a post-purchase price drop. These returns can be induced by two factors. Some customers strategically return their purchased products in order to reorder them at a lower price and absorb the price difference. Other customers return products because price can be an indicator of implied quality and thus affect their decision. In particular, in the apparel retail industry, customers who have limited knowledge of a product's true quality may infer that more expensive products are of higher quality (Gerstner 1985). In this case, if customers observe a post-purchase price drop, their confidence in the product may decline, and thus they may decide not to keep the product. We call these price-related returns *opportunistic returns*, and the larger the price uncertainty, the larger the benefit of returns. It is worth emphasizing that, when customers decide whether to return a purchased product, they are aware of the price information after their purchase. Hence, the benefit of returns is related to the *post-purchase* price change.

Fit-related returns are often regarded as exogenous to the pricing decision in both industry practice and the academic literature (e.g. Anderson et al. 2009). However, previous research has not considered that price-related returns can have important implications on pricing. Following our previous discussion of product returns, if a strategic customer observes a post-purchase price drop, he or she may choose to return the product so as to exploit the price difference. Firms mark down prices frequently in order to attract more customers, but if this triggers opportunistic returns, firms not only suffer from decreased net sales, but also incur higher logistic costs and inventory management costs. As mentioned above, customers have access to the post-purchase price information when deciding whether to return the product. Hence, we empirically test whether post-purchase price drops lead to more returns. We formalize this in the following hypothesis:

Hypothesis 1 *All else equal, returns are positively associated with post-purchase price drops.*

Moreover, it has been shown in previous studies that returns occur more frequently for products with higher prices. For example, Anderson et al. (2006) show that lower prices lead to additional consumer surplus, which reduces the likelihood that a customer will return an item. The model in Anderson et al. (2009) implies the same result that consumers are less likely to return a lower-priced item. In contrast, if a product is bought with a higher price, consumers are more likely to return it when there is any dissatisfaction, because of greater benefits of returning it (or greater regret of not returning it). The aforementioned studies drew the conclusion using data from the United States, and we hypothesize the same scenario for emerging markets:

Hypothesis 2 *All else equal, returns are positively associated with product price.*

Furthermore, the level of discounts also plays an important role in affecting product returns. Given the same list price, the higher the discount level, the lower the benefit of returns. Moreover, even if the monetary benefit of returning a product is identical, we anticipate that more heavily discounted items are less likely to be returned, due to the lower likelihood of a further price drop and the extra utility of getting a deal. For example, the return probability of a full-priced USD 50 t-shirt can be quite different from that of a half-price t-shirt with a list price of USD 100. Prospect theory states that people choose among probabilistic alternatives based on the potential values of losses and gains (Kahneman and Tversky 1979), and people often attribute more weight to losses than gains. In our setting, returning a highly discounted product may result in little gain and high opportunity costs, while returning an undiscounted product may lead to potential gains. Thus, we make the following hypothesis to empirically test whether discount levels affect product returns:

Hypothesis 3 *All else equal, returns are negatively associated with discounts.*

In addition to the above analyses of returns, we also study the relationship between dynamic pricing and the choice of payment method. In particular, we investigate the usage of COD. From the firm's perspective, COD not only leads to higher return rates but also induces longer collection cycles, both of which are costly to the firm. Thus, whether dynamic pricing results in more COD transactions can have a profit impact. From the customers' perspective, COD can be used strategically in order to reduce potential return costs, if customers believe a return is likely. And if hypothesis 1 is supported, customers tend to return more if they observe a post-purchase price drop. It is worth emphasizing that at the time of choosing the payment method, customers only have the price information up to the moment of purchase. Therefore, at the time of purchase, customers would form an expectation of whether the price will drop after the purchase, and would then decide which payment method to use. Combining these, we conjecture that an *expected* price drop leads to a higher usage of COD. This is formalized in the following hypothesis:

Hypothesis 4 *A higher expectation of price drops leads to more COD transactions.*

EMPIRICAL SETTING AND DATA

Data Description

Our empirical analysis focuses on the online apparel retail industry in India. There are a number of reasons why this industry is a suitable empirical setting given our research objectives. First, the online retail industry is economically important. In 2015, e-commerce sales in India amounted to approximately USD 16 billion, and it is estimated that by 2020 the online retail market could expand by more than seven-fold (The Economist 2016). Second, the use of dynamic pricing is prevalent in online retailing in India (see Rai 2015; Punit 2015; Dalal 2016). Third, returns are common in online retailing with significant cost implications. According to one source referring to returns in the United States, "returned goods are collected, sorted and resold by logistics companies, and resold to liquidators such as Shorewood Liquidators at approximately 10-20 cents on the dollar" (Tang 2016). The apparel industry exemplifies these cost considerations, given volatile demand as well as a high rate of return. Finally, India not only has a large number of holiday sales and discounts, but also heavily features the COD payment method popular in emerging economies, which helps identify the driving forces of returns and enables an analysis of strategic choice of payment method.

We obtained data from a leading online apparel retailer in India (name omitted due to confidentiality). The company has focused on the online retail of clothing and accessories for more than five years. Since India is mostly tropical, the temperature is steadily high all year around. As a result, the company does not change its product assortment significantly, which implies a low level of seasonality. For the same reason, the company regularly replenishes best-selling products, making availability less of an issue. The company has frequent sales events, either pre-announced or in the form of flash sales, but which specific products are on sale is typically unpredictable.

Our data consist of sales records in the 10 most popular categories from this online apparel merchant over the period from September 1 to November 30 in 2015. For each transaction, we observe the date it took place, the stock-keeping unit (SKU) ID of the product sold, and an encrypted customer ID that we can track over time. We are also able to observe the payment method (whether the customer paid online or by COD), and whether the product was returned. One thing to note is that the company does not distinguish non-acceptance from a normal return in their data, so a declined delivery counts as a return.

The data include each SKU's category (e.g. t-shirt, casual shoes, etc.) as well as gender information (men, women, boys, girls, unisex). For each transaction, we also observe the following variables related to price and discounts: transacted price (*Price*) is the price a customer pays out of pocket; merchant recommended price (*MRP*) is the "original price" listed at the online store; and discount (*Discount*), which is the rupee discount amount applied to the purchase (MRP minus price). We are also interested in the relative discount level instead of the absolute dollar amount, so we divide *Discount* by *MRP* to obtain *DiscountPercentage*, which is the "% off" seen by customers at the shopping website.

In total, we have 2,805,986 transactions in our data set, covering 161,920 products and 1,118,651 customers. The transacted price has a mean of 878.58 Indian rupees (about USD 13) and a standard deviation of 647.46 Indian rupees (about USD 10). Cash on delivery was used in 66.6 percent of transactions, which is in line with the popularity of COD in India. Overall, about 20 percent of transactions are marked "returned." Such a return rate is considered moderate in the apparel retail industry in developed countries. Nevertheless, in our interviews with company executives, they indicated a concern that such a high return rate had a negative effect on profitability, particularly due to high logistics costs in India.

One important observation of the data set is that there is significant variation in discount percentages across products. The average discount rate is 42.8 percent, which means on average a product is sold at 57.2 percent of the list price. Table 1 summarizes total revenue and quantity sold at different discount percentages. We can see that, in our sample, only 16.2 percent of total revenue and 11.7 percent of the quantity sold was at full price (zero discount); more than half of products sold were at a discount rate between 21 percent and 40 percent.

[Insert Table 1 about here.]

Measuring the Extent of Dynamic Pricing

The firm that provided data for this research makes frequent use of sale events to attract customers and enhance demand. Examples include daily flash sales that offer roughly 20 percent off, weekly weekend sales at about 40 percent off, and various festive sales at about 60 percent off. In the data, we confirm the prevalence of discounts as 88.3 percent of transactions have nonzero discounts.

The mean discount is 670.13 Indian rupees (about USD 10) or 43 percent off full prices. We also find evidence of the prevalence of price changes: among products that had been purchased at least twice, 86.41 percent have price changes.

In order to understand the impact of dynamic pricing, we begin by quantifying the extent of dynamic pricing. In particular, given that we are measuring the impact on customers, we look for measures that can be calculated by customers. While there are some intuitive and widely used measures such as standard deviation or the coefficient of variation (CV), we are more interested in transaction-level dynamic-pricing measures, because our data set features transaction-level details. In this paper, we propose a novel binary measure that is computed for each transaction. We investigate the instances of price changes for those products purchased more than once during the period of our study, and we are able to track the price histories in the following way. For each transaction, we look for a future purchase record of the same product, and we calculate in how many days its price drops. Then we create a binary variable indicating whether the price drops in two days. In order to filter out negligible price drops, we modify the above metric by applying a 10 percent price-drop threshold of the transaction price. We use the resulting binary variable, "a 10 percent price drop in 2 days", or $\mathbb{1}^{\{\text{PriceDrop}\}}$, as the proposed metric. An example of creating such variables is shown in Table 2. The binary variable $\mathbb{1}^{\{\text{PriceDrop}\}}$ generated above has a mean of 0.3581 and a standard deviation of 0.4794 among all transactions in our period of study. This is to say that 35.81 percent of transactions involve prices dropping by at least 10 percent in 2 days.

[Insert Table 2 about here.]

The greatest advantage of the metric $\mathbb{1}^{\{\text{PriceDrop}\}}$ is that it is at the transaction level, so it can take different values for different transactions even for the same product. Also, it makes sense for customers to track prices after purchase over a two-day window, because typically the delivery time is two days for the company we study. We perturb the thresholds of 10 percent and 2 days to generate more binary variables for robustness checks in our main analysis, and we find that the choices of different thresholds do not affect our results. The summary statistics of these variables are shown in Table 3. For example, the proportion of transactions with a price drop of more than 10 percent in 2 days is 38 percent. As we change these two thresholds, the proportion of transactions with a future price drop changes accordingly: as we look further in time, or when we relax the price-drop threshold, the proportion of transactions with a future price drop increases. In the main analysis, we perform extensive robustness checks as described later to show that all our results are robust to the perturbations.

[Insert Table 3 about here.]

The proposed binary variable $\mathbb{1}^{\{\text{PriceDrop}\}}$ is subject to censoring. If we do not observe a transaction in our dataset, we are unsure about the price at that time. For example, it is possible that price dropped in reality, but because no one purchased at that price in our dataset, we are not aware of that price drop. Fortunately, our data is a representative sample of all transactions in India during our period of study, and the sample volume is sufficiently large for the censoring issue to be considered minimal.

Another issue is that, based on our definition, there are two types of transactions that always have $\mathbb{1}^{\{\text{PriceDrop}\}} = 0$: those transactions for products purchased only once during the period of our study, and the final transaction for all other products. These transactions provide no variation to our regression analysis, and hence are dropped from our analysis. In total, 161,920 such transactions are dropped, which is 5.7 percent of all 2,805,976 transactions. The remaining number of observations is 2,644,066. Retaining these transactions does not qualitatively change our results.

Lastly, when we analyze the choice of payment method that a customer has to make at the time of purchase, we cannot use the *post-purchase* binary variable $\mathbb{1}^{\{\text{PriceDrop}\}}$, because at the time of purchase the customer has not observed subsequent price changes. Following a similar logic, we define a *pre-purchase* transaction-specific variable, $ProbPriceDrop$, to model the probability of a future price drop perceived by the customer at the time of purchase. Admittedly, we can not observe $ProbPriceDrop$ in our data, so we will use multiple econometric models to obtain various predictions of $ProbPriceDrop$, and then use the predicted values in our analysis of payment-method choice.

ECONOMETRIC APPROACH AND RESULTS

In this section, we present the econometric models we use to test our hypotheses. We begin by providing some direct evidence to support our hypotheses and discuss why this direct evidence only represents a portion of the strategic customer behavior that we study. Then we set up a choice model of returns and apply the resulting logistic regression to test the first three hypotheses about product returns. In addition, we set up a choice model of payment options and apply an additional logistic regression to test the last hypothesis. Lastly, in order to address the potential endogeneity issue, we propose a joint estimation model and conclude that our hypotheses remain supported.

Direct Evidence

We first provide some direct evidence in support of our hypotheses. We start with Hypothesis 1, which states that post-purchase price drops increase the probability of returns. We are able to identify those purchases that were returned and subsequently repurchased by the same customers, and we define a binary variable, $ReturnedAndRepurchased$, accordingly. During our 3-month period of study, there were 14,706 purchases that were returned and repurchased, with 50.04 percent of them repurchased at a strictly lower price. Possible reasons for the remaining return-and-repurchase behavior may include fit uncertainty.

If return-and-repurchase instances are cases of opportunistic returns, we can directly test whether post-purchase price drops affect opportunistic returns. The following regression equation captures the effect of post-purchase price drops on return-and-repurchase transactions.

$$ReturnedAndRepurchased_i = b_1 + b_2 \mathbb{1}_i^{\{\text{PriceDrop}\}}, \tag{1}$$

where $\mathbb{1}_i^{\{\text{PriceDrop}\}}$ indicates that transaction i had a price drop of at least 10 percent within 2 days.

If Hypothesis 1 is supported, we expect the coefficient b_2 to be positive, so that post-purchase price drops increase the probability of a product being returned and repurchased. The result in Table 4 shows that the effect is indeed positive and significant.

[Insert Table 4 about here.]

Opportunistic returns can occur even in cases where the product is not repurchased. There are at least two other possibilities. First, customers may return a purchased product because they observe that a close substitute is on sale. For example, if a customer purchases a pair of Nike shoes at USD 100, and then sees that the price of a pair of similar Adidas shoes drops from USD 100 to USD 50, he or she may choose to return the Nike shoes and purchase the Adidas ones. Such returns take place because of the dynamic pricing on the Adidas shoes, but the firm suffers from the returns of the Nike shoes. The direct evidence we provide above does not include this possibility. Moreover, it is also possible that strategic customers make a purchase with the intent to return it if they observe a post-purchase price drop, but they keep the product in the end because the price drop does not occur. In this case, had the firm offered a discount after the purchase, the customer would have returned and repurchased the product at the expense of the firm. In conclusion, the analysis we presented above provides a lower bound on the extent of opportunistic return behavior.

In addition, we provide a model-free, graphical illustration in support of Hypothesis 3, which states that returns are negatively associated with discounts. We first cluster all the transactions in the data into several sets defined by $DiscountPercentage$ and COD, with $DiscountPercentage$ discretized into 9 bins with increments of 10 percent. Then we compute the mean return rates in each of these clusters and plot them in Figure 1. As the figure shows, the mean return rates exhibit a monotonically decreasing pattern with discount percentage for both COD and non-COD transactions, which shows that higher discounts lead to lower return rates. Hence, Hypothesis 3 is supported in Figure 1.

[Insert Figure 1 about here.]

Direct evidence of return-and-repurchase instances due to post-purchase price drops, as well as the pattern of return rates with respect to discount rates, partially supports our hypotheses. In the next subsection, we propose a choice model of returns in order to formally test our hypotheses regarding product returns using logistic regressions.

A Choice Model of Returns

Following the approach of Anderson et al. (2009), we propose a choice model that derives the underlying logic of customers returning purchased products.

Consider customer i who is deciding in period t whether to return or keep an item. We assume that

$$U(\text{return})_{it} = -R_{it}, \tag{2}$$

$$U(\text{keep})_{it} = \mu_{it} + \epsilon_{it}, \tag{3}$$

where

$$\mu_{it} = \beta_i' X_t. \tag{4}$$

The utility of returning an item is simply the return cost, so the utility is non-positive. The return cost includes not only physical costs such as shipping and transportation, but also mental or psychic costs such as hassle.

The utility of keeping an item consists of two components. First, μ_{it} is the deterministic utility that is known by both the researcher and the consumer before the purchase. The vector X contains variables that explain the mean utility. Second, ϵ_{it} is a standard econometric error term that is known to the customer but is not observed by the researcher. For example, time-varying shocks to preferences are captured by the error term. An important note is that we consider the matter of fit to be modeled into the error term. This is because our focus is on price-related returns, so fit-related returns are treated as exogenous. This rationale is supported by the industry practitioners we interviewed.

Based on this model, a customer will keep the item if

$$\mu_{it} + R_{it} + \epsilon_{it} > 0. \tag{5}$$

Therefore, the probability of keeping the item is

$$\begin{aligned}\text{Pr(Keep)} &= Pr(\mu_{it} + R_{it} + \epsilon_{it} > 0) \\ &= \text{Pr}(\epsilon_{it} > -(\mu_{it} + R_{it})) \\ &= \text{Pr}(\epsilon_{it} > -(\beta_i' X_t + R_{it})).\end{aligned} \tag{6}$$

The probability of returning the item is

$$\text{Pr(Return)} = Pr[\epsilon_{it} \leq -(\beta_i' X_t + R_{it})]. \tag{7}$$

If we assume that ϵ_{it} are distributed $i.i.d.$ type I extreme value, we have

$$\text{Pr(Return)} = \frac{\exp[-(\beta_i' X_t + R_{it})]}{1 + \exp[-(\beta_i' X_t + R_{it})]}. \tag{8}$$

Hence, the logistic regression model is as follows:

$$\text{logit } (\text{Pr}(Return = 1)) = R + \beta X + \text{error term}. \tag{9}$$

Equation (9) is in a general form. We will specify our variables of interests to test our hypotheses in the next subsection.

Analysis of Returns

We formulate our estimation model from equation (9), beginning with inspecting the first term on the right-hand side, R. As specified in equation (2), R represents the return cost, which is affected by the payment method. Specifically, if the customer uses COD, he or she can decline delivery at no cost, so the return cost experienced by the customer is much lower. As a result, we model the return cost as the sum of a baseline cost plus a term that is related to the use of COD:

$$R = \beta_0 + \beta_5 COD. \tag{10}$$

Next, as equation 4 states, the term βX represents the mean utility of purchase that is known by both the researcher and the customer before purchase. In our study, the price-drop indicator, $\mathbb{1}^{\{\text{PriceDrop}\}}$, the discount amount, $DiscountAmount$, and the transaction price, $Price$, are the three focal variables that affect mean utility.

Hence, we use the following logistic regression equation to test hypotheses 1–3, which correspond to the relationships between return rates and post-purchase price drops, product prices, and discount amount, respectively. Since our data indicate whether each purchase was returned, we are able to conduct the analysis at the transaction level. The logistic model is as follows:

$$\begin{aligned} \text{logit}\left(\Pr(Return_i = 1)\right) = \beta_0 + \beta_1 \mathbb{1}_i^{\{\text{PriceDrop}\}} + \beta_2 Price_i + \beta_3 DiscountAmount_i \\ + \beta_4 CONTROLS_i + \epsilon_i^{Return}. \end{aligned} \tag{11}$$

We include payment method in the control variables, since it is not the main focus of our analysis. Other controls include the product category of each transaction. If there is a post-purchase price drop ($\mathbb{1}^{\{\text{PriceDrop}\}} = 1$), the mean utility of keeping the good becomes smaller, and thus a return is more likely. Hence, Hypothesis 1 predicts that the sign of β_1 should be positive, indicating that return rates are positively associated with post-purchase price drops. Similarly, Hypothesis 2 predicts that $\beta_2 > 0$, indicating that return rates are positively associated with product price; Hypothesis 3 predicts that $\beta_3 < 0$, indicating that return rates are negatively correlated with discount levels.

[Insert Table 5 about here.]

The regression results are summarized in Table 5. All three of our hypotheses are supported. From the marginal-effects analysis, a future price drop increases the probability of a return from 19.3 percent to 19.4 percent. Furthermore, products with higher prices or lower discounts are more likely to be returned: an increase in product price of 100 Indian rupees leads to a 0.1 percent increase in return rates; an increase in discount amount of 100 Indian rupees leads to a 0.2 percent decrease in return rates.

While the estimated effect of a price drop on return probability may look small, its economic significance should not be overlooked. According to a survey (McKinsey & Company 2017), the average EBITDA margin in the fashion retail industry is 9.0 percent to 9.5 percent in 2016, and the average net profit margin is 3.0 percent to 5.0 percent. The profit margin for online apparel retailers is often lower or even negative. In our case, if we assume a net profit margin of 3 percent, and if the loss associated with a return is assumed to be 60 percent of the selling price, then an increase of 0.1 percent in return probability can lead to a decrease of 2 percent of total profit, which constitutes a non-negligible decline.

We perform various robustness checks and find that our results are robust to other specifications. First, in the regression model specified above, we define $\mathbb{1}^{\{\text{PriceDrop}\}}$ to be 1 if there is an observed price drop in the data greater than 10 percent of the transaction price within 2 days of purchase. We expand the observation window to 5 days and 10 days. The results in columns (2)–(3) in Table 6 indicate that all of our three hypotheses continue to hold.

Second, instead of defining $\mathbb{1}^{\{\text{PriceDrop}\}}$ to be 1 if there is an observed price drop in the data greater than 10 percent of the transaction price within 2 days of purchase, we perturb the price drop threshold to 5 percent and 20 percent. The results in columns (4)–(5) of Table 6 indicate that all of our three hypotheses continue to be supported.

[Insert Table 6 about here.]

Moreover, while our logistic specification includes several relevant control variables, we can add many more fixed-effect controls in order to address potential endogeneity concerns. Table

7 reports all the results we obtain, with column (1) as the baseline model. In column (1), the fixed-effect controls include payment method (COD) and product category.

In order to control for product quality and other product-specific unobservables, we can add product fixed effects to the baseline model (and drop the category fixed effects). The results are presented in column 2. Note that the coefficient of the binary price drop variable is three times larger than the baseline model, which shows that opportunistic returns may happen more often controlling for product quality.

In order to control for customer-specific unobservables (for example, whether customers self-select to become discount chasers), we can add customer fixed effects (recall that we do not have any demographic information of customers in our dataset). The results are presented in column 3. The coefficients are the same as the baseline model, which means our results remain valid even if customers may be heterogeneous.

In order to control for both product-specific unobservables and customer-specific unobservables, we can add both product fixed effects and customer fixed effects (and drop category fixed effects). The results are presented in column 4. The coefficients are similar to those in column 2, which also points to the direction that the estimate of opportunistic returns can be conservative in the baseline model.

Finally, on top of the "full model" in column 4, we further add a day of the week variable to control for time of purchase. The results are presented in column 5, which are very similar to those in column 6.

In conclusion, in the regression results in Table 7, the estimates of effect sizes change slightly, but the significance of parameters shows that all of our three hypotheses remain supported.

[Insert Table 7 about here.]

Lastly, in order to rule out a potential concern that customer segmentation drives our results (for example, those customers who only use COD are fundamentally different from other customers), we conduct the analysis restricting our attention to those purchases only from customers who have used both COD and credit cards during our period of study. There are 654,548 transactions in this sub-dataset, which is 24.8 percent of the original dataset. The regression equation is Equation 11 as before, and we report the marginal effects at means in Table 8. Once again, the regression coefficients remain significant, and we conclude that our hypotheses are supported using the sub-dataset where customers have the possibility to use both payment methods.

[Insert Table 8 about here.]

In summary, we have presented evidence for the significance of factors affecting return behavior. Our main finding is that post-purchase price drops lead to higher return rates, and this finding is robust to various alternative specifications. Other findings include a positive effect of product prices and a negative effect of discount levels on return rates.

The Drivers of Payment-Method Choice

In this section, we formulate a discrete choice model to investigate how customers choose their payment methods. Ideally, when customers decide whether to purchase a product, they take into account which payment method they want to use. In order to focus on the choice of payment method, we assume customer i has decided to purchase product k, and the customer only needs to make a choice between using COD and using online payment methods such as credit cards.

Formally, conditional on purchase, customer i decides whether to pay by credit card $(j = 0)$ or to use COD $(j = 1)$. Both methods have the same shipping cost (usually free), but there are other characteristics affecting customer i's choice.

We denote customer i's utility of choosing payment method j to be

$$U_{ij}(X_j) = V_{ij}(X_j) + \epsilon_{ij}, \tag{12}$$

where X_j represents all the observable characteristics, and ϵ_{ij} is only observed by customer i.

Customer i then chooses to use COD if and only if

$$U_{i1} \geq U_{i0}, \tag{13}$$

i.e.,

$$V_{i1} - V_{i0} \geq \epsilon_{i0} - \epsilon_{i1}. \tag{14}$$

If we assume that ϵ_{ij} are distributed *i.i.d.* type I extreme value across i, and we normalize V_{i0} to be 0, then we have:

$$\text{Pr}(COD = 1|X) = \frac{\exp(X\alpha)}{1 + \exp(X\alpha)}. \tag{15}$$

Among all the observable characteristics in X, one variable of interest is the customers' predicted probability of a price drop in the near future, $ProbPriceDrop$. If dynamic pricing is applied frequently, there are more anticipated price drops from the customers' point of view. If customers anticipate that there may be a potential price drop, they may consider the possibility of an opportunistic return. Since purchasing with COD can lower the cost of opportunistic returns, customers are more likely to use COD. Hence, in the following econometric model,

$$\text{logit}\ (\text{Pr}(COD_i = 1)) = \alpha_0 + \alpha_1 ProbPriceDrop_i + \alpha_2 CONTROLS_i + \epsilon_i^{COD}, \tag{16}$$

if expected price drops indeed lead to higher COD usage, Hypothesis 4 predicts that the coefficient of $ProbPriceDrop$ will be positive. This regression is at the transaction level. The dependent binary variable COD_i takes 1 if transaction i is a COD transaction. We continue to use $Price$ and category fixed effects as controls. A challenge is how to recover the anticipated probability of a price drop for transaction i at the time of purchase.

Note that the variable $ProbPriceDrop$ is different from the variable of interest in Hypothesis 1, $\mathbb{1}^{\{\text{PriceDrop}\}}$. In Hypothesis 1, customers decide whether to return a purchased product based on *post-purchase* price drops. Here, in Hypothesis 4, customers decide which payment method to use at the time of purchase, based on (the probability of) *expected* price drops. However, since we are unable to observe the anticipated probability of a price drop for transaction i, we can use price-drop (binary) indicator $\mathbb{1}^{\{\text{PriceDrop}\}}$ observed in the data to replace $ProbPriceDrop$, if we assume that customers have perfect foresight (see Li et al. 2014). The regression result is presented in column (0) of Table 9. The coefficient α_1 is positive and significant, and the average marginal effect analysis suggests that a perfectly foreseen price drop increases the probability of COD usage by 2.5 percent, which confirms our Hypothesis 4.

[Insert Table 9 about here.]

As a robustness check, we propose the following models in which customers form their prediction models to predict $ProbPriceDrop$. We assume customers first estimate the following candidate models using the full data and then use the predicted probability as their predictions of $ProbPriceDrop$: $ProbPriceDrop = \mathbb{1}^{\{\widehat{\text{PriceDrop}}\}}$.

$$\text{logit}\ (\Pr(\mathbb{1}_i^{\{\text{PriceDrop}\}} = 1)) = \beta_1 Cat_i + \epsilon_i \tag{16.1}$$

$$\text{logit}\ (\Pr(\mathbb{1}_i^{\{\text{PriceDrop}\}} = 1)) = \beta_1 Cat_i + \beta_2 ListPrice_i + \beta_3 Gender_i + \beta_4 TotalSales_i + \epsilon_i \tag{16.2}$$

$$\begin{aligned}\text{logit}\ (\Pr(\mathbb{1}_i^{\{\text{PriceDrop}\}} = 1)) = {} & \beta_1 Cat_i + \beta_2 ListPrice_i + \beta_3 Gender_i + \beta_4 TotalSales_i \\ & + \beta_5 Price_i + \beta_6 DiscountPctg_i + \epsilon_i \end{aligned}\tag{16.3}$$

The binary variable $\mathbb{1}^{\{\text{PriceDrop}\}}$ takes 1 if there was a price drop larger than 10 percent for transaction i in 2 days. For the independent variables, the first model only uses category- level information, so that all transactions in one category would have the same probability of a future price drop. The second model uses category-level information as well as product characteristics, so that all transactions of one product would have the same probability of a future price drop. The third model further incorporates transaction-specific information, so that each transaction would have a different probability of a future price drop.

After estimating these three models, we obtain the predicted probability of a future price drop $\hat{\mathbb{1}^{\{\text{PriceDrop}\}}}$, and then plug $ProbPriceDrop = \hat{\mathbb{1}^{\{\text{PriceDrop}\}}}$ into Equation (16). The estimates of coefficient α_1 are reported in columns (1)–(3) of Table 9. The positive and significant coefficients of $ProbPriceDrop$ support our Hypothesis 4.

Another potential concern is that it is possible that some customers only purchase using a certain payment method under certain circumstances. For example, for those customers with relatively low income and no credit card, they may purchase only during a sales event, and all their purchases would be COD purchases. In order to prevent this possibility affecting our results, we again restrict our attention to those purchases only from customers who have used both payment methods. We apply the perfect foresight model to the sub-dataset, and we find that the regression coefficients remain positive and significant in column (0′) of Table 9, which shows that Hypothesis 4 remains supported using the sub-dataset where customers have used both payment methods during our period of study. In all cases, COD is more likely to be used when prices are expected to drop.

Another robustness check is to address a potential endogeneity concern with Hypothesis 4. Hypothesis 4 posits that a higher expectation of price drops leads to more COD transactions. Although we have emphasized the important distinction between the *post-purchase* price-drop measure $\mathbb{1}^{\{\text{PriceDrop}\}}$ in Hypothesis 1 and the *expected* price-drop measure $ProbPriceDrop$ in Hypothesis 4, one may be concerned about the endogeneity problem of the payment-method choice and the return decision being correlated. In other words, the endogeneity concern suggests that, when customers decide which payment method to use, their reasoning may carry over to determine whether to return the product. In our econometric model, this is to say that the following two equations may have correlated errors and need to be jointly estimated:

$$
\begin{cases}
\text{logit}\left(\Pr(Return_i = 1)\right) = \beta_0 + \beta_1 COD_i + \beta_2 \mathbb{1}_i^{\{\text{PriceDrop}\}} + \beta_3 DiscountAmount_i \\
\qquad\qquad + \beta_4 Price_i + \beta_5 CONTROLS_i + \epsilon_i^{RET} \qquad \text{(11 revisited)} \\
\\
\text{logit}\left(\Pr(COD_i = 1)\right) = \alpha_0 + \alpha_1 ProbPriceDrop_i + \alpha_2 CONTROLS_i + \epsilon_i^{COD}. \qquad \text{(16 revisited)}
\end{cases}
$$

Using the potential outcome framework, we model the choice of payment method COD as an endogenous treatment effect on the outcome variable $Return$. In order to estimate the average treatment effect (ATE) of an endogenous binary-treatment variable COD, we can set up a linear probability model. We assume that COD_i is a binary-treatment variable that stems from an unobservable latent variable $COD_i^{\star}$. Finally, we use the product category information as the control variable. The linear probability model is as follows:

$$
\begin{cases}
Return_i = \beta_0 + \beta_1 COD_i + \beta_2 \mathbb{1}_i^{\{\text{PriceDrop}\}} + \beta_3 DiscountAmount_i + \beta_4 Price_i \qquad (17) \\
\qquad\qquad + \beta_5 Category_i + \epsilon_i^{RET} \\
\\
COD_i^{\star} = \alpha_0 + \alpha_2 ProbPriceDrop_i + \alpha_3 DiscountAmount_i + \alpha_4 Price_i \\
\qquad\qquad + \alpha_5 Category_i + \epsilon_i^{COD} \\
\\
COD_i = 1, \text{ if } COD_i^{\star} > 0 \\
\qquad\qquad 0, \text{ otherwise} \\
\\
\begin{pmatrix} \epsilon^{RET} \\ \epsilon^{COD} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right].
\end{cases}
$$

In order to predict the $ProbPriceDrop$ in the second equation, we use the richest transaction-level model described in the previous subsection. We first estimate the coefficients from the following linear regression equation. We then use the predicted $Prob\hat{Price}Drop$ as $ProbPriceDrop$ to plug in the second equation above.

$$\begin{aligned} ProbPriceDrop_i =& \beta_1 Category_i + \beta_2 ListPrice_i + \beta_3 Gender_i + \beta_4 TotalSales_i \\ &+ \beta_5 Price_i + \beta_6 DiscountPctg_i + \epsilon_i^{\mathbb{1}\{\text{PriceDrop}\}}. \end{aligned} \tag{18}$$

We follow the method of deriving a maximum likelihood estimator for a constrained endogenous-switching model in Maddala (1986). The regression results are presented in Table 10. The significance of ρ suggests that endogeneity can be a valid concern, and the negative sign shows that a customer who chooses to pay with COD would be more likely to return the product in the future. Nevertheless, this joint estimation model still supports our hypotheses. The model predicts that a post-purchase price drop leads to 0.2 percent more returns, which is larger than the corresponding estimate without controlling for endogeneity. Hence, correcting for endogeneity increases the estimated strength of the relationship between post-purchase price drops and return probabilities.

[Insert Table 10 about here.]

CONCLUSION AND DISCUSSION

This paper studies two forms of previously undocumented customer behavior: opportunistic returns and strategic choice of payment method, both as consequences of dynamic pricing. In the context of online apparel retailing in India, we show that post-purchase price drops cause the return rate to increase, keeping all else constant. We also show that higher prices lead to more returns, while higher levels of discounts result in fewer returns. Lastly, we show that dynamic pricing, or a pre-purchase anticipation of future price drops, leads more consumers to pay through cash on delivery.

To complement our findings, we ran a brief survey on Amazon Mechanical Turk, asking participants from India about their online shopping behavior. According to the survey responses, over 15 percent of the participants said that they have made opportunistic returns, and about 20 percent confirmed that they have declined deliveries of cash on delivery purchases because of post-purchase price drops. These results corroborate our findings, and suggest that opportunistic returns are broadly relevant in online retailing in an emerging market context.

While our findings identify a downside of dynamic pricing, further research is needed to adequately perform a cost-benefit analysis. This would require information on how much net demand is generated by either universal or personalized markdowns. Also relevant would be the precise cost to the firm induced by a product return. It is likely that the benefit of a properly designed dynamic-pricing policy outweighs the cost and thus leads to higher profits. Nevertheless, our results suggest that higher return rates and more COD usage can be a source of hidden costs for dynamic pricing, which introduces research opportunities to study the optimal dynamic pricing model that accounts for this strategic behavior.

Some limitations of our analysis point to additional opportunities for further research. For example, it could be interesting to estimate the operational costs associated with opportunistic returns, which we have not addressed due to data constraints. Further research could also target strategic customers who have made opportunistic returns and involve the design of randomized experiments to study their behavior.

From the firm's perspective, one possible policy to mitigate opportunistic returns is to offer price matching. If the customer who observes a price drop after the purchase can obtain the price difference without returning and reordering the product, the firm can save a considerable amount of logistic costs. However, such a price-matching policy can backfire if only a small portion of customers exhibit opportunistic return behavior. In fact, U.S. online retailing firms Amazon and Walmart, both of which had previously offered price matching within seven days of purchase, eventually discontinued their price matching policy (Hui 2016). Another practice that the firm can implement is offering more personalized discounts to non-strategic customers in order to stimulate demand, while committing more to prices for those customers with previous opportunistic return behavior. In order to counter the strategic choice of payment method, firms can increase the inconvenience of using COD, for example by issuing store vouchers instead of cash if a return happens.

In sum, our paper points out two hidden costs of dynamic pricing: opportunistic returns and strategic choice of payment method. We show that the magnitude of the impact can be sizable, and we believe the implications are valuable for both practitioners and academics.

REFERENCES

Agatz, N. A., Fleischmann, M., and Van Nunen, J. A. (2008). E-fulfillment and multi-channel distribution–A review. *European Journal of Operational Research*, 187(2):339–356.

Altug, M. S. and Aydinliyim, T. (2016). Counteracting strategic purchase deferrals: The impact of online retailers' return policy decisions. *Manufacturing & Service Operations Management*, 18(3):376–392.

Anderson, E. T., Hansen, K., and Simester, D. (2009). The option value of returns: Theory and empirical evidence. *Marketing Science*, 28(3):405–423.

Anderson, E. T., Hansen, K., Simester, D., and Wang, L. K. (2006). How price affects returns: The perceived value and incremental customer effects. *Unpublished Manuscript, Northwestern University, Evanston, IL.*

Aviv, Y. and Pazgal, A. (2008). Optimal pricing of seasonal products in the presence of forward-looking consumers. *Manufacturing & Service Operations Management*, 10(3):339–359.

Balasubramanian, K. and Drake, D. (2015). Service Quality, Inventory and Competition: An Empirical Analysis of Mobile Money Agents in Africa. *Harvard Business School Technology & Operations Mgt. Unit Working Paper*, (15-059).

Banjo, S. (2013). Rampant returns plague e-retailers. *Wall Street Journal*. Retrieved from https://www.wsj.com/articles/rampant-returns-plague-eretailers-1387752786, Accessed: 03/14/2017.

Bell, D. R., Gallino, S., and Moreno, A. (2017). Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science*, (forthcoming).

Besanko, D. and Winston, W. L. (1990). Optimal price skimming by a monopolist facing rational consumers. *Management Science*, 36(5):555–567.

Bower, A. B. and Maxham, J. G. (2012). Return shipping policies of online retailers: normative assumptions and the long-term consequences of fee and free returns. *Journal of Marketing*, 76(5):110–124.

Cachon, G. P. and Swinney, R. (2009). Purchasing, pricing, and quick response in the presence of strategic consumers. *Management Science*, 55(3):497–511.

Coase, R. H. (1972). Durability and monopoly. *The Journal of Law & Economics*, 15(1):143–149.

Confederation of Indian Industry (2016). E-commerce in India: A game changer for the economy. Retrieved from https://www2.deloitte.com/in/en/pages/technology-media-and-telecommunications/articles/e-commerce-in-india.html, Accessed: 03/14/2017.

Credit Suisse (2016). Emerging consumer survey 2016. Retrieved from https://www.credit-suisse.com/corporate/en/articles/news-and-expertise/emerging-consumer-survey-201604.html, Accessed: 03/14/2017.

Dalal, M. (2016). Flipkart, Amazon to restart discount war this month. *livemint.com*. Retrieved from http://www.livemint.com/Companies/Nl4l1L69Le0nlIeVtlCBLO/Online-retailers-set-to-restart-discount-wars.html, Accessed: 03/14/2017.

Das, G. (2014). Cash-on-delivery: Necessary evil. *Business Today*. Retrieved from http://www.businesstoday.in/magazine/cover-story/cash-on-delivery-impact-on-e-commerce-companies-customers/story/202680.html, Accessed: 03/14/2017.

DeHoratius, N., Mersereau, A. J., and Schrage, L. (2008). Retail inventory management when records are inaccurate. *Manufacturing & Service Operations Management*, 10(2):257–277.

DeHoratius, N. and Raman, A. (2008). Inventory record inaccuracy: an empirical analysis. *Management Science*, 54(4):627–641.

Gallino, S. and Moreno, A. (2017). The value of fit information in online retail: Evidence from a randomized field experiment. *Manufacturing & Service Operations Management*, (forthcoming).

Gerstner, E. (1985). Do higher prices signal higher quality? *Journal of Marketing Research*, pages 209–215.

Guide, V. D. R., Souza, G. C., Van Wassenhove, L. N., and Blackburn, J. D. (2006). Time value of commercial product returns. *Management Science*, 52(8):1200–1214.

Hui, R. (2016). With changes to price-matching, Amazon and Walmart usher a new era of retail. *techcrunch.com*. Retrieved from https://techcrunch.com/2016/06/13/with-changes-to-price-matching-amazon-and-walmart-usher-a-new-era-of-retail/, Accessed: 03/14/2017.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, pages 263–291.

Kannan, P. and Kopalle, P. (2001). Dynamic pricing on the internet: Importance and implications for consumer behavior. *International Journal of Electronic Commerce*, 5(3):63–83.

Li, J., Granados, N., and Netessine, S. (2014). Are consumers strategic? Structural estimation from the air-travel industry. *Management Science*, 60(9):2114–2137.

Liu, Q. and Van Ryzin, G. J. (2008). Strategic capacity rationing to induce early purchases. *Management Science*, 54(6):1115–1131.

Maddala, G. S. (1986). *Limited-dependent and qualitative variables in econometrics*. Number 3. Cambridge university press.

McKinsey & Company (2017). The state of fashion 2017. Retrieved from http://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/the%20state%20of%20fashion/the-state-of-fashion-mck-bof-2017-report.ashx, Accessed: 03/14/2017.

Nair, H. (2007). Intertemporal price discrimination with forward-looking consumers: Application to the us market for console video-games. *Quantitative Marketing and Economics*, 5(3):239–292.

Nair, R. P. (2013). Cash-on-delivery hurts bottom line of cos like Flipkart, Snapdeal due to extra associated costs. *The Economic Times*. Retrieved from http://economictimes.indiatimes.com/industry/services/retail/cash-on-delivery-hurts-bottom-line-of-cos-like-flipkart-snapdeal-due-to-extra-associated-costs/articleshow/25192740.cms, Accessed: 03/14/2017.

Nasiry, J. and Popescu, I. (2012). Advance selling when consumers regret. *Management Science*, 58(6):1160–1177.

Ng, S. and Stevens, L. (2015). Where your unwanted Christmas gifts get a second life. *Wall Street Journal*. Retrieved from https://www.wsj.com/articles/where-your-unwanted-christmas-gifts-get-a-second-life-1451212201, Accessed: 03/14/2017.

Ofek, E., Katona, Z., and Sarvary, M. (2011). "Bricks and clicks": The impact of product returns on the strategies of multichannel retailers. *Marketing Science*, 30(1):42–60.

Papanastasiou, Y. and Savva, N. (2014). Dynamic pricing in the presence of social learning and strategic consumers. *Management Science*.

Parker, C., Ramdas, K., and Savva, N. (2016). Is IT enough? Evidence from a natural experiment in India's agriculture markets. *Management Science*, 62(9):2481–2503.

Petersen, J. A. and Kumar, V. (2009). Are product returns a necessary evil? Antecedents and consequences. *Journal of Marketing*, 73(3):35–51.

Punit, I. S. (2015). The moment of reckoning for India's online shopping websites is here: The festive season sales. *Quartz India*. Retrieved from https://qz.com/513002/indian-e-commerce-companies-are-preparing-from-their-biggest-ever-test-the-online-festive-season-sales/, Accessed: 03/14/2017.

PwC India (2015). E-commerce in India: Accelerating growth. Retrieved from http://www.pwc.in/assets/pdfs/publications/2015/ecommerce-in-india-accelerating-growth.pdf, Accessed: 03/14/2017.

Rai, S. (2015). In India's brutal Diwali e-commerce war, Paytm bets on digital wallets as the transactional future. *The Forbes*. Retrieved from https://www.forbes.com/sites/saritharai/2015/10/28/in-indias-brutal-diwali-ecommerce-war-paytm-bets-on-digital-wallets-as-the-transactional-future/#7c12b2454f83, Accessed: 03/14/2017.

Randall, T., Netessine, S., and Rudi, N. (2006). An empirical examination of the decision to invest in fulfillment capabilities: A study of internet retailers. *Management Science*, 52(4):567–580.

Rao, S., Griffis, S., and Goldsby, T. (2011). Failure to deliver? Linking online order fulfillment glitches with future purchase behavior. *Journal of Operations Management*.

RBI (2016). Concept paper on card acceptance infrastructure. Retrieved from `https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=840`, Accessed: 03/14/2017.

Sahay, A. (2007). How to reap higher profits with dynamic pricing. *MIT Sloan Management Review*, 48(4):53–60.

Sharmal, S. (2016). Indian e-commerce industry's growth comes to a halt, Snapdeal worst hit. *Gadgets Now*. Retrieved from `http://www.gadgetsnow.com/tech-news/Indian-e-commerce-cart-hits-a-plateau/articleshow/52933341.cms`, Accessed: 03/14/2017.

Shulman, J. D., Coughlan, A. T., and Savaskan, R. C. (2009). Optimal restocking fees and information provision in an integrated demand-supply model of product returns. *Manufacturing & Service Operations Management*, 11(4):577–594.

Shulman, J. D., Coughlan, A. T., and Savaskan, R. C. (2011). Managing consumer returns in a competitive environment. *Management Science*, 57(2):347–362.

Singh, S. (2016). Ecommerce leaders' annual GMV growth rate only 11%; E-tail industry exhausted? *IndianOnlineSeller.com*. Retrieved from `http://indianonlineseller.com/2016/06/ecommerce-leaders-annual-gmv-growth-rate-only-11-e-tail-industry-exhausted/`, Accessed: 03/14/2017.

Soysal, G. P. and Krishnamurthi, L. (2012). Demand dynamics in the seasonal goods industry: An empirical analysis. *Marketing Science*, 31(2):293–316.

Su, X. (2007). Intertemporal pricing with strategic customer behavior. *Management Science*, 53(5):726–741.

Su, X. (2009). Consumer returns policies and supply chain performance. *Manufacturing & Service Operations Management*, 11(4):595–612.

Swinney, R. (2011). Selling to strategic consumers when product value is uncertain: The value of matching supply and demand. *Management Science*, 57(10):1737–1751.

Tang, C. (2016). Avoiding the boomerang effect of online sales returns. Retrieved from `http://blogs.anderson.ucla.edu/global-supply-chain/2016/03/avoiding-the-boomerang-effect-of-online-sales-returns.html`, Accessed: 03/14/2017.

The Economist (2016). Online retailing in India: The great race. Retrieved from `http://www.economist.com/news/briefing/21693921-next-15-years-india-will-see-more-people-come-online-any-other-country-e-commerce`, Accessed: 03/14/2017.

Tunca, T. I. and Zhu, W. (2017). Buyer intermediation in supplier finance. *Management Science*, Forthcoming.

Wood, S. L. (2001). Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *Journal of Marketing Research*, 38(2):157–169.

Yuan, H. and Han, S. (2011). The effects of consumers' price expectations on sellers' dynamic pricing strategies. *Journal of Marketing Research*, 48(1):48–61.

Table 1: Total Revenue and Quantity Sold at Different Discount Rates

Discount percentage (%)	Revenue (%)	Quantity sold (%)
0	16.2	11.7
1-20	24	19
21-40	51.9	58.2
41-60	7.7	10.7
>60	0.2	0.3
Total	100	100

Table 2: An Example of Creating a Dynamic Pricing Measure Using the Price History of One Product

Order date	Price	Days until next price drop	Whether price drops in 2 days	Days until next 10% price drop	Whether price drops by 10% in 2 days ($\mathbb{1}^{\{\text{PriceDrop}\}}$)
11/20	494.98	1	1	1	1
11/21	419.48	1	1	1	1
11/22	377.53	2	1	4	0
11/24	375.58	0	1	2	1
11/24	372.65	2	1	2	1
11/26	218.13	NA	0	NA	0
11/27	335.58	NA	0	NA	0
11/28	402.7	NA	0	NA	0

Table 3: Summary Statistics for Various Dynamic Pricing Measures

	Price drop by 5% in 2 days	**Price drop by 10% in 2 days**	Price drop by 20% in 2 days	Price drop by 10% in 5 days	Price drop by 10% in 10 days
Mean	0.461	0.380	0.255	0.481	0.565
s.d.	0.498	0.485	0.436	0.500	0.496

Table 4: Impact on Returned and Repurchased Transactions

	$ReturnedAndRepurchased$
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.001^{***}
	(0.0001)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: Logistic Regression Results of Returns

	Dependent variable:	
	Return	
	Coefficients	*Marginal Effects*
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.007^{**}	0.001^{**}
	(0.003)	(0.0005)
Price	0.00008^{***}	0.00001^{***}
	(0.000003)	(0.0000005)
DiscountAmount	-0.0002^{***}	-0.00002^{***}
	(0.000003)	(0.0000006)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6: Robustness Check 1 – Various Price-Drop Measures

	Dependent variable: Return				
	Price-Drop Measures				
	(1) by 10% in 2 days	(2) by 10% in 5 days	(3) by 10% in 10 days	(4) by 5% in 2 days	(5) by 20% in 2 days
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.001^{**}	0.001^{**}	0.002^{***}	0.001^{*}	0.001^{**}
	(0.0005)	(0.0005)	(0.0008)	(0.0006)	(0.0004)
Price	0.00001^{***}	0.00001^{***}	0.00001^{**}	0.00001^{***}	0.00001^{***}
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)
DiscountAmount	-0.00002^{***}	-0.00002^{***}	-0.00002^{**}	-0.00002^{***}	-0.00002^{***}
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)

Note: marginal effects and standard errors are reported
*p<0.1; **p<0.05; ***p<0.01

Table 7: Robustness Check 2 – Adding More Controls

	Dependent variable:				
	Return				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.001^{**}	0.003^{***}	0.001^{*}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Price	0.00001^{***}	0.00000	0.00001^{***}	0.00001^{**}	0.00001^{**}
	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
DiscountAmount	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}	-0.00002^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
Payment Method	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	No	Yes	No	No
Product FE	No	Yes	No	Yes	Yes
Customer FE	No	No	Yes	Yes	Yes
Day of the Week	No	No	No	No	Yes

Note: marginal effects and standard errors are reported
*p<0.1; **p<0.05; ***p<0.01

Table 8: Robustness Check 3 – Using the Sub-Dataset of Customers with Both Payment Options

	Dependent variable:	
	Return	
	Marginal Effect	*Marginal Effect*
	(1) Original Dataset	(2) Sub-Dataset
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.001^{***}	0.002^{***}
	(0.0005)	(0.001)
Price	0.00001^{***}	0.00001^{***}
	(0.00000)	(0.00000)
DiscountAmount	-0.00002^{***}	-0.00002^{***}
	(0.00000)	(0.00000)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 9: Regression Results of COD Usage Against Probability of Price Drop

	Dependent variable:				
	COD				
	(0) Perfect foresight	(1) Category level	(2) Product level	(3) Transaction level	(0′) Sub-dataset
ProbPriceDrop	0.025***	0.745***	0.133***	0.057***	0.004***
	(0.001)	(0.006)	(0.002)	(0.002)	(0.001)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 10: Joint Linear Probability Regression Results

	Dependent variable:	
	Return	COD
COD	0.103^{***}	
	(0.004)	
$\mathbb{1}^{\{\text{PriceDrop}\}}$	0.002^{***}	
	(0.0005)	
ProbPriceDrop		0.123^{***}
		(0.005)
DiscountAmount	-0.006^{***}	-0.0003
	(0.0001)	(0.0005)
Price	0.007^{***}	-0.070^{***}
	(0.0005)	(0.002)
ρ	-0.081^{***}	
	(0.007)	
σ	0.399^{***}	
	(0.0002)	
Wald test of $\rho = 0$:	$\chi^2(1) = 142.91$	$Prob > \chi^2 = 0.0000$
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 1: Return Rates, Discount Levels, and Payment Methods