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Effects of Price Reductions on Customer Return Behavior

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Abstract

Online retailers vary product prices over time, in order to influence customer purchase behavior. Problem is, customers might also change their return behavior based on observed and paid prices. Price reductions thereby potentially affect returns both of purchases made during the price reduction and of purchases made before the price reduction but which are still eligible for returning. This study investigates the influence of price reductions on product returns using a unique database of a large European online retailer containing more than 83.7 million purchases and more than 37.5 million returns in over 300 product categories. Results show that price reductions can both foster and lower product returns, depending on prior customer behavior. While price reductions lead to more returns for customers that have returned due to a price reduction before, price reductions lead to fewer returns for customers that have not returned due to a price reduction before. For search goods, utilitarian and gift categories, these effects are weakened. We discuss managerial implications based on the result that accounting for the impact of price reductions on product returns helps online retailers to increase their profitability.

Keywords: Online retailing, product returns, e-commerce, promotion, discount, survival model

Introduction

Online retailers dynamically adapt prices for promotional or strategic reasons in order to respond to demand changes, inventory level, and competitors' prices (Elmaghraby and Keskinocak 2003; Fisher, Gallino, and Li 2018; Grewal 2011; Grewal et al. 2010). While numerous studies have shown that a decrease in price fosters sales (Bijmolt, Van Heerde, and Pieters 2005; Gupta 1988) and changes price and brand perception (e.g. Blattberg, Briesch, and Fox 1995; Rao 2009), the influence of price reductions on product returns has received much less attention – even though product returns are crucial for the profitability of online retailers (Minnema et al. 2018).

When shopping online, customers first have to decide whether or not to order the product, and once they have received the product whether or not to keep it, as they usually have the ability to return products without any reason within a certain period of time (Consumer World 2018), which, in some jurisdictions, is even legally required (European Union 2011). Price reductions may influence these product returns in two ways. First, a price reduction can potentially influence returns of purchases that were made *during* a price reduction (Petersen and Kumar 2009) – i.e., purchases for which the customer has paid less than the regular price. In addition, there is some evidence that post-purchase price reductions can also influence returns of purchases made *before* a price reduction (Bandi et al. 2018) – i.e., purchases for which the customer has paid a higher price than the post-purchase reduced price. That is, price promotions might accidentally motivate customers to return within the return period, thereby possibly replacing the regular-price product with the same product, newly ordered at a reduced price.

With this study, we contribute to the literature by examining the effects of price reductions (a) *during* or (b) *after* the product purchase on the customer's decision to keep or return the product. In addition, we assess the role of prior customer return behavior in this process, and investigate to what extent these effects hold across a range of product categories, depending on category characteristics. In particular, we address the following research questions:

- To what extent are products more (or less) likely to be returned when they are purchased during a price reduction?
- To what extent are products more (or less) likely to be returned when there is a price reduction after the purchase?
- To what extent do customers become used to return products with either price reduction condition?
- To what extent are the effects of price reductions different across product categories, and which category characteristics have an impact on these differences?

We approach our research questions with a very large and unique database, containing more than 80 million purchases in over 300 product categories during a period of three years from a major European generalist online retailer. The database contains most product categories that are popular in online retailing, and allows identifying both the strength and direction of the effect of price reductions on returns in general, as well as category-specific effects. It thus provides a rich set of empirical generalizations on the effects of price reductions on product returns and important managerial insights for the contemporary online retailing environment.

Theoretical background

The customer purchase decision is part of a multi-step customer buying decision process (e.g., Kotler et al. 2019). Before purchasing a product, customers search for information and evaluate alternatives. After purchasing a product, customers obtain and evaluate their purchase and possibly return it (Bijmolt et al. 2019). Price reductions are influential in both pre- and post-purchase steps (Bijmolt, Van Heerde, and Pieters 2005; Cooke, Meyvis, and Schwartz 2001) and might in both cases influence returning.

Price reductions during (pre-)purchase

Before customers purchase a product, they search for information and evaluate alternatives. Here, the product price plays a crucial role. A reduced price – due to a temporary price promotion or a permanent price decrease from the original price – during (pre-)purchase renders previously unaffordable products affordable and extends the choice set, on a consumer level (Howell, Lee, and Allenby 2016). As a consequence, on an aggregate level, price reductions generally increase short-term sales (Bijmolt, Van Heerde, and Pieters 2005; Gupta 1988).

Price reductions, however, likely also have an impact on return behavior. On the one hand, when the product does not fully match customers’ expectations, a lower purchase price could convince customers to keep the product. Petersen and Kumar (2009) have empirically shown that products on sale are returned less than regularly priced products. In addition, and more generally, products with a higher price are returned more (Hess and Mayhew 1997). Therefore, price reductions might result in lower return rates. On the other hand, however, price reductions can increase impulse buying (Kacen, Hess, and Walker 2012; Xu and Huang 2014). Impulsively purchased products, in turn, might be more susceptible to be returned. Therefore, price reductions might also result in more returns. In sum, we propose two competing hypotheses for the effect of price reductions on product returns:

H1a: Customers are *more* likely to return a product that is purchased during a price reduction.

H1b: Customers are *less* likely to return a product that is purchased during a price reduction.

Price reductions after purchase

After purchasing a product, customers obtain and evaluate their purchase and, as a result of the evaluation, might return the product. At the evaluation stage, price reductions that came into effect after the purchase, might still be seen by customers and influence product evaluation and consequently returning. This is likely driven by two distinct processes.

The first process relates to strategic customer behavior. Customers might be aware of the fact that product prices are dynamic over time. For example, after a purchase is made, customers are often still exposed to cookie-based online advertising for products they have been looking for in the recent past, also from the retailer at which they made the purchase, possibly with a lower price than they paid. An economic and rational customer could consequently monitor the post-purchase product price of a purchase and factor it into the decision of whether or not to return the product. If a post-purchase price reduction is substantial, such a customer will want to return – and re-order – their purchase because it allows for saving money. This line of reasoning has been posited by Khouja, Ajjan, and Liu (2019) and Bandi et al. (2018) and the resulting returns have been termed “opportunistic returns”. Bandi et al. (2018) have shown that returns and re-purchases are happening in practice. Since opportunistic returns can only happen when there is a post-purchase price reduction, we expect post-purchase price reduction to increase returns.

A second processes leading to increased returns due to post-purchase price reductions relates to dissonance-reducing behavior: after purchase, customers evaluate their purchase by comparing perceived performance with prior expectations (Kotler et al. 2019). When expectations are not fully met, customers try to confirm the value of their purchase by outside sources and thereby reduce dissonance (Mitchell and Boustani 1994). One effective way to do so is to read other customers’ reviews (Liu et al. 2019) on the site of the retailer. By that, customers, who are already on the fence of keeping or returning the product, are prone to discover post-purchase price reductions. Post-purchase price reductions are a prototypical example of inducing a feeling of regret (Cooke, Meyvis, and Schwartz 2001; Simonson 1992; Tsiros and Hardesty 2010; Zeelenberg and Pieters 2007). Regret “is the emotion that we experience when realizing or imagining that our current situation would have been better, if only we had decided differently” (Zeelenberg and Pieters 2007, p. 3). A reduced price creates a salient, lower price reference, customers will perceive their own, higher, purchase price as unfair (Campbell 1999) and experience regret. In addition, the willingness to purchase the product at its regular price can decrease (Chang, Gao, and Zhu 2015) and customers might want to undo their current purchase, as regret leads to “strong wishes to undo the current situation” (Zeelenberg and Pieters 2007, p. 3). In sum, price reductions post-purchase are expected to increase product returns.

H2: Customers are more likely to return a product with a post-purchase price reduction.

Prior returners of products with reduced prices

Human beings have the tendency to repeat past behavior (Neal et al. 2012). Customer behavior is no exception: research shows that customers show recurring behavior with regards to purchases, response to promotions, and product returns (Petersen and Kumar 2009, 2015; Shah, Kumar, and Kim 2014). In line with this, once customers have started to return products that are reduced in price during or after purchase, they may continue to do so.

Prior returners of products with reduced prices during purchase

First, for purchases during a price reduction, we hypothesized above that they could lead to both more or less returns. The argument for increased returns is that price reductions during purchase lead to more impulse purchases, which have a higher chance to be returned (Kacen, Hess, and Walker 2012; Xu and Huang 2014). The tendency of impulse buying has been linked to a consumer’s personality traits by numerous studies (e.g. Sharma, Sivakumaran, and Marshall 2010; Wells, Parboteeah, and Valacich 2011). In a meta-analysis, Amos et al. (2014) find that dispositional factors (i.e. relatively permanent personal predispositions) and the interaction between dispositional and situational factors are the two strongest predictors of impulse buying. This supports the notion that some customers are more prone to purchase products with a reduced price on an impulse than other customers, and, by consequence, are more likely to regret and return the product. And if they have done so in the past, they are – due to the stability of dispositional traits – more likely to do so in the future:

H3: Customers are more likely to return a product purchased during a price reduction, the more they have returned products purchased during a price reduction, in the past.

Prior returners of products with reduced prices after purchase

For returns due to price reductions after purchase, customers will likely show recurring behavior, too. In general, customers habitually respond to promotions (Shah, Kumar, and Kim 2014). Some customers might develop a habit to look out for price reductions after purchase in order to return and re-purchase a product, i.e., they unconsciously and automatically re-visit the online retailer after the purchase and find post-purchase price reductions. Automatic, unconscious processes "drive the bulk of consumer behavior" (Martin and Morich 2011, p. 493). According to Shah, Kumar, and Kim (2014), the habit of responding to promotions and the habit of returning are significantly and positively correlated. We hypothesize that customers learn to return products with a post-purchase reduced price and therefore are more likely to return a product with a price reduction after purchase, when they did so in the past:

H4: Customers are more likely to return a product with a post-purchase price reduction, the more they have returned products with a post-purchase price reduction, in the past.

Product category heterogeneity

The influence of price reductions on returns – whether during purchase or post-purchase – likely varies across categories. That is because category characteristics influence (a) the customer buying and return process, and (b) the perceived value of a price reduction (Bell, Chiang, and Padmanabhan 1999). For example, if there is a price reduction in categories with consumable products (e.g. diapers or cosmetics), customers can decide to stockpile additional products, whereas they will be less likely do so in categories with durable products (e.g. furniture) and instead send the product back to benefit from a lower price (Macé and Neslin 2004).

Extant literature provides a whole range of category characteristics that influence customers' buying and/or return processes, and that thus may also have a moderating effect on the influence of price reductions (during or after purchase) on product returns. We classify these characteristics into three groups. The first group comprises category characteristics that arise solely from the products itself (bulky, durable, search good, and seasonal). The second group includes category characteristics related to the main reasons for customers to purchase or use the product (gift, hedonic, and utilitarian). Finally, the third group deals with category characteristics that arise not from any individual product but all products combined, i.e., the assortment (average price, number of articles, and number of brands). Regarding product features, products being bulky, durable, search goods, or seasonal might alter the impact of price reductions on returning. Returning bulky products is more effortful and a lower price needs to outweigh the effort of returning (Kim and Wansink 2012). Durables, on the other hand, are not suited for stockpiling and customers need to send products back in order to make use of a price reduction (Krishna 1994; Macé and Neslin 2004). Search goods can be evaluated before purchase, possibly diminishing the role of price reductions to reduce regret and, as a consequence, return propensity (Hong and Pavlou 2014; Petersen and Kumar 2009).

Seasonal products have the highest value at the beginning of the season and a returning for getting a price reduction must outweigh the additional delivery time (Soysal and Krishnamurthi 2012). But, purchase of seasonal products is prone to regret (Petersen and Kumar 2009) and thereby could have a higher return rate – especially so, if regret is increased by a price reduction after purchase.

Regarding product use, products purchased given as gifts, being hedonic or being utilitarian might alter the impact of price reductions on returning. Gifts are often impractical to return (Petersen and Kumar 2009), and cost savings might generally be less important as gifts are seen as symbols for relationship value (Larsen and Watson 2001). Although it is impossible to know whether a certain product was gifted, certain product categories are more likely given as gifts whereas others are "deemed inappropriate" (Larsen and Watson 2001), justifying the inclusion on the category level. Hedonic product spending is usually harder to justify than utilitarian product spending (Okada 2005), possibly increasing the relevance of price reductions for wanting to keep (for purchases made during price reductions) or return the product (for purchases with post-purchase price reductions).

Regarding the product assortment within a category, the average price and the number of articles and brands might have an influence, since higher number of brands and articles lead to increased trial of new products due to price reductions (Bawa, Landwehr, and Krishna 1989) which, in turn, may increase uncertainty and return probability. Higher category pricing, finally, increases the importance of price reductions and might strengthen the effect of price reductions on dis- or encouraging returns.

To our knowledge, this is the first paper to investigate the impact of product heterogeneity in terms of product category characteristics on the relationship between (post-purchase) price reductions and return behavior. Since our effort is to a large extent exploratory and includes a broad set of category characteristics with theoretical evidence sometimes being sparse, we abstain from formulating hypotheses and approach this as an empirical question.

Data

Sample

To assess the impact of price reductions on product returns, we base our empirical analysis on a vast and unique database of a large European online retailer. The retailer sells a wide range of products in numerous categories, including fashion, electronics, home appliances, cosmetics, and furniture.

Our data consists of three sets of information. First, we have order and return data of all the retailer's clients over a period of 3 years (from the third quarter of 2016 until the second quarter of 2019). In this period, customers made more than 83.7 million purchases and more than 37.5 million returns of over 565,000 unique products. For every order, we have detailed order and product information (e.g., date, delivery fee, product category, price, price reduction during purchase), and basic demographic customer information (age, gender). All orders can be associated to a unique customer, which allows us to follow individual purchase and return histories. We use a one-year initialization period to set variables pertaining to customer's prior return behavior (see below), and use the remaining two years of data for model estimation.

Second, we have daily pricing information – including regular and current (potentially reduced) price – of all products during the observational period, amounting to several billion price points in total. Each product price is coupled with a unique product identifier, which allows associating the first dataset with the second. In accordance with the length of the return period, we link the records of the product purchases with product prices starting from the date of the order until 31 days after the order.

Lastly, we have a category-level dataset on category characteristics. This dataset includes qualitative information on whether a product category is durable (or consumable), frequently gifted, seasonal, utilitarian, hedonic, bulky, and consists of search good (or experience goods). These characteristics have been evaluated on a binary basis for each category by three independent expert judges. All three judges agreed in 51% of the cases, and in the other 49% majority judgment was followed. In addition to the manually-coded category characteristics, we derive category-level control variables from the order dataset. These variables include the number of articles in the category, the number of brands in the category, and the average product price in the category, which we include as standardized variables (i.e., mean-centered and divided by the standard deviation).

Per category, we use a sample of up to 100,000 orders (less, if the category contains fewer orders). In addition, we exclude categories with a very low number of orders (< 10,000). The exclusion of the latter is warranted given their proneness to unstable estimation results due to multicollinearity and other data issues. Its impact on the overall estimates is limited as these categories represent less than 2% of all orders.

Variables

For our analysis of product returns, we have a range of purchase- and category-level variables at our disposal. First and most importantly, we observe whether or not a product has been purchased during a price reduction, and whether or not there is a price reduction after the purchase. Both variables are based on three variants of the product price: the regular price, the current price, and the purchase price. The regular price is based on the recommended retailer price and is relatively static. The current price is the daily fluctuating price of the product based on promotional choices and rebates by the retailer. The purchase price is the price that the customer paid for a product and is thus equal to the current price at the time of purchase. We define a purchase during a price reduction as the situation in which the purchase price is lower than the regular price. A post-purchase price reduction, in turn, is defined as the situation in which the current price is lower than the purchase price. This varies per day, since the current price also varies per day (see Figure 1).

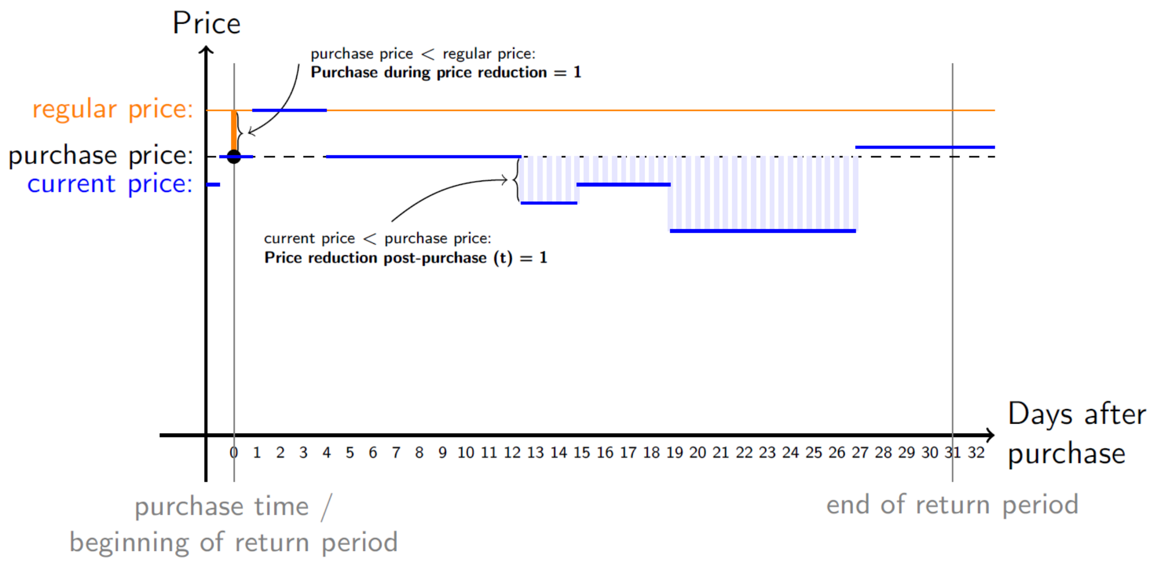

Figure 1: Diagram of how the regular price, current product price, and purchase price lead to a purchase during a price reduction and price reductions post-purchase

In addition, we calculate several 'prior behavior' variables, which indicate whether a customer (1) returned any purchase before, (2) returned a purchase that was made during a price reduction before, or (3) returned a purchase during a post-purchase price reduction before – and potentially could do the same with the current purchase. In particular, that means that, for (2), the purchase needs to be made during a price reduction and, for (3), there needs to be a price reduction post-purchase (see Table).

We differentiate whether or not a customer engaged in the respective behavior in the past *at all*, i.e., one time or more ('prior returner' variables), and next whether customers engaged in the respective behavior in the past *lightly*, i.e., one or two times ('light returner' variables), versus whether customers engaged in the respective behavior in the past *heavily*, i.e., three or more times ('heavy returner' variables).

Furthermore, we observe several control variables at customer and order level. Customer control variables are age and gender, and order control variables include information about the order size, delivery cost, and several seasonality controls. For the analysis of category effects, we have information about category size, price level, and a range of manually coded category characteristics.

Table 1: Dependent and independent variables used in the analysis

Variable	Definition	Data summary	
Purchase-level variables			
Return (at day t)	Whether or not the purchase was returned (at day t of the return period)	Frequency: Mean t: SD t:	32.79% 11.01 days 5.24
Purchase during price reduction	If the purchase price is lower than the regular price	Freq.:	49.47%
Price reduction post-purchase (at day t)	If the current price at day t is lower than the purchase price	Mean: SD:	3.34 days 6.62
Prior returner with: purchase during price reduction	If the purchase price is lower than the regular price and the customer has returned a purchase with a purchase price lower than the regular price before	Freq.:	33.37%
Light returner with: purchase during price reduction	If the purchase price is lower than the regular price and the customer has returned a purchase with a purchase price lower than the regular price 1-2 times before	Freq.:	6.20%
Heavy returner with: purchase during price reduction	If the purchase price is lower than the regular price and the customer has returned a purchase with a purchase price lower than the regular price 3 or more times before	Freq.:	27.17%
Prior returner with: price reduction post-purchase (at day t)	If the current price at day t is lower than the purchase price and the customer has returned a purchase with a current price lower than the purchase price before	Freq.:	5.62%
Light returner with: price reduction post-purchase (at day t)	If the current price at day t is lower than the purchase price and the customer has returned a purchase with a current price lower than the purchase price 1-2 times before	Freq.:	1.81%
Heavy returner with: price reduction post-purchase (at day t)	If the current price at day t is lower than the purchase price and the customer has returned a purchase with a current price lower than the purchase price 3 or more times before	Freq.:	3.82%
Basket price	Total price of products ordered together with the product	Mean: SD:	205.27 263.76
Basket size	Total number of products ordered together with the product	Mean: SD:	5.77 6.30
Purchase price	Product purchase price	Mean: SD:	50.28 99.17

Delivery fee	Cost of delivering the order	Mean: SD:	.08 .47
$Year_2$	Whether the order was placed in the second year of the two-year estimation period	Freq.:	48.63%
$Month_2$, $Month_3$, …, $Month_{12}$	If the order was placed in February, March, …, December	Freq.:	4.62% - 10.41%
Customer-level variables			
Prior returner	If the customer has returned any purchase before	Freq.:	76.68%
Light returner	If the customer has returned 1-2 purchases before	Freq.:	9.23%
Heavy returner	If the customer has returned 3 or more purchases before	Freq.:	67.45%
Age	Customer's age (mean-centered)	Mean: SD:	42 years 11.61
$Gender_{male}$	Whether customer's gender is male	female: male:	80.08% 19.92%
Category-level variables			
Product features			
Durable	Category with: Products that are usually used 3 years or longer (dummy variable)	Freq.:	41.48%
Bulky	Category with: Products that are difficult to handle due to size or weight (dummy variable)	Freq.:	9.92%
Search good	Category with: Products with attributes that can almost fully be evaluated online before purchase (dummy variable)	Freq.:	58.52%
Seasonal	Category with: Products with large seasonal demand fluctuations (dummy variable)	Freq.:	13.49%
Product use			
Gift	Category with: Products often purchased as a gift (dummy variable)	Freq.:	9.92%
Hedonic	Category with: Products purchased mainly for pleasure or fun (dummy variable)	Freq.:	39.44%
Utilitarian	Category with: Products purchased mainly for a functional task (dummy variable)	Freq.:	53.18%
Assortment related			
Average price	Average price of product purchases product in the category	Mean: SD:	58.85 93.93
Number of articles	Number of articles in the category (that were purchased at least once during the observation period)	Mean: SD:	1351.25 2653.55
Number of brands	Number of brands in the category (that were purchased at least once during the observation period)	Mean: SD:	38.66 35.16

Methodology

Our primary aim is to study the effect of price reductions on product returns. While product return data have been used by several papers before (e.g. Hess and Mayhew 1997; Minnema et al. 2016; Petersen and Kumar 2009), no earlier product return paper, to our knowledge, assessed the effect of a dynamic independent variable that varies along the return period. This introduces an additional modelling challenge, as we will discuss below.

Base duration model

The dependent variable product return and the independent variable price promotions can both take multiple values during the return period, i.e., at any day $t = [1, \ldots, 31]$ after purchase. For example, a purchased product might have two price reductions, first from day 1 to 10 and then from day 20 to 30 after purchase – while being returned at day 10. Our model then needs to account for a possible influence of the first price reduction on the product return but not of the second price reduction, as it happened after the return and thus cannot have an impact on the return probability anymore.

A simple way to model product returns as a binary outcome variable is using a logit model. This could be done by aggregating the data over the return period into one observation per purchase (returned yes or no), or by including each day after the purchase up to the day of the product return or end of the return period as independent observations. However, both approaches lead to biased estimates[1].

As a solution, we use a survival model, which can naturally incorporate time-varying information in the dependent and independent variables (Aalen, Borgan, and Gjessing 2008).

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[1] First, when aggregating daily post-purchase price reduction information over the whole return period into a single variable, returns at any day d_R would partly be explained by price reductions at day $d_i > d_R$, going against causality. On the other hand, when aggregating post-purchase price reduction information only up to the day of return d_R, we would risk a biased estimate: over time, both the aggregated chance of returning and the aggregated chance of price reductions increase, resulting in a spurious positive relationship. Second, treating each day as independent biases the standard error – and either goes against causality, when including the whole return period, or gives purchases a different weighting, when only including days up to the product return.

The survival rate *S(t)* refers to the expected proportion of individuals who did not yet encounter an event – in our case returning a product – at time t, i.e.,

$$S(t) = P(T > t) \quad T\text{: random variable denoting the time before return (possibly infinite)} \#(1)$$

which can be transformed into the hazard rate $\lambda(t)$,

$$\lambda(t) = -\frac{S'(t)}{S(t)} = \lim_{dt \to 0} \frac{1}{dt} \frac{P(t \leq T < t + dt)}{S(t)}, \#(2)$$

where S'(t) is the derivative of the survival rate S(t), i.e.,

$$S'(t) = \frac{d}{dt} S(t). \#(3)$$

Intuitively, the hazard rate $\lambda(t)$ denotes the probability of the event, i.e., a product return, happening in t and is conditional on not having returned in the past (Aalen, Borgan, and Gjessing 2008; Klein 2014). Thereby, it accounts for the fact that the event – i.e., a product return – can only happen once.

Survival regression models can be formulated in several ways. The most commonly used Cox model has the restriction of proportional hazard ratios, i.e., that a covariate has the same relative effect over time (Klein 2014). For example, if a price reduction after 5 days increases product returns by 10%, so would a price reduction after 25 days. This restriction is not sensible in our case (and ignoring it could lead to serious bias, see e.g., Box-Steffensmeier and Jones 2004; Hosmer, Lemeshow, and May 2008). Therefore, we resort to a spline-based model, as originally suggested by Royston and Parmar (2002), which allows for non-proportional hazards.

Royston and Parmar's (2002) model incorporates survival as a spline function for the baseline hazard plus a sum of splines for $1, \dots, D$ time-dependent effects (thus allowing for non-proportional hazards) plus all time-independent effect of covariates $\boldsymbol{x}$ multiplied by the coefficients $\boldsymbol{\beta}$:

$$\ln\left(-ln\big(S(t;\boldsymbol{x})\big)\right) = s(\ln(t)\,|\boldsymbol{\gamma}) + \sum_{j=1}^{D} s\big(\ln(t)\,|\boldsymbol{\delta_j}\big)x_j + \boldsymbol{x\beta}\#(4)$$

where the spline function $s(\cdot)$ is defined as

$$s(\ln(t)\,;\boldsymbol{p}) = \sum_{k=1}^{K} B_k\,(\ln(t))p_k\#(5)$$

and $B_k(\ln(t))$ is a natural spline basis with K degrees of freedom (Clements 2019; Royston and Lambert 2011). This model is a generalization of the Weibull parametric survival model with the benefit of allowing for non-monotonic hazards. We allow for time-dependent effects for all focal variables using the most flexible functional form of each effect over time.

Analysis models

Using the model from equation (4) as a basis, we formulate three models to estimate the effect of price reductions on product returns. First, we estimate the general effect of price reductions on product returns. Thus, in this model, we do not distinguish between customers who have returned earlier or not. Based on equation (4), the our first model (I) then is:

$$\ln\left(-\ln\left(S\big(t;\boldsymbol{x}_{,\boldsymbol{t},\boldsymbol{i}}\big)\right)\right) = s(\ln(t)\,|\boldsymbol{\gamma}) + s(\ln(t)\,|\boldsymbol{\delta_1})x_{1,i} + s(\ln(t)\,|\boldsymbol{\delta_2})x_{2,t,i} + \boldsymbol{x}_{,\boldsymbol{t},\boldsymbol{i}}\boldsymbol{\beta}\#(6)$$

with:

t, i: days since purchase for a purchase i,

$\boldsymbol{\gamma}$: vector of baseline spline coefficients,

$\boldsymbol{\beta}$: vector of intercept and coefficients for all included variables,

$\boldsymbol{x}_{,\boldsymbol{t},\boldsymbol{i}} = (1, x_{1,i}, x_{2,t,i}, x_{3,i}, \dots, x_{22,i})$: vector of a constant and variables with data for purchase i at time t and particularly:

$x_{1,i}, x_{2,t,i}$: Whether or not the product has been purchased during a price reduction; the product price is reduced (further) at day t

$\boldsymbol{\delta_1}, \boldsymbol{\delta_2}$: vectors of spline coefficients for time-dependent effects of the focal variables $x_{1,i}$ and $x_{2,t,i}$, respectively.

Second, we assess whether prior returners, i.e., customers who have been returning products with a price reduction before, behave differently to other customers. Therefore, we extend model (I) by two additional variables, pertaining to prior returning with price reductions. That is, we extend $\boldsymbol{x}_{,t,i}$ by $x_{23,i}, x_{24,t,i}$: Whether or not the customer has returned a product purchased at a reduced price before *and* the product is purchased during a price reduction; the customer has returned a product with a post-purchase price reduction before *and* the product price is reduced (further) at day t. As before, we allow the effect of both variables to vary over time and, therefore, include two additional spline functions. We denote the resulting model as model (II).

Third, we assess which customers drive the effect of prior returners. For that, we split prior returners into light returners, who have returned one or two times, and heavy returners, who have returned three or more times. That is, we replace $x_{23,i}$ and $x_{24,t,i}$ from model (II) by four new variables $x_{25,i}, x_{26,t,i}, x_{27,i}, x_{28,t,i}$. First, the variables $x_{25,i}$ and $x_{26,t,i}$ indicate: whether or not the customer has returned a product purchased at a reduced price 1-2 times before *and* the product is purchased during a price reduction; whether or not the customer has returned a product with a post-purchase price reduction 1-2 times before *and* the product price is reduced (further) at day t. Second, the variables $x_{27,i}$ and $x_{28,t,i}$ indicate: whether or not the customer has returned a product purchased at a reduced price 3 or more times before *and* the product is purchased during a price reduction; whether or not the customer has returned a product with a post-purchase price reduction 3 or more times before *and* the product price is reduced (further) at day t. Again, we allow the effect of these variables to vary over time and include the related spline functions. We denote the resulting model as model (III).

Model estimation

We estimate models (I)-(III) separately for purchases in each product category. Using per-category estimation, we are able to use a combined sample that is 10 to 100 times larger than when estimating one model for all categories together[2]. For estimation, we have to set the degrees of freedom of the spline parameters. We follow recommendations by Royston and Lambert (2011) and start with K = 5 degrees of freedom for the splines in most categories and then reducing the degrees of freedom in small categories, where otherwise there would be identification issues. We exclude a number of smaller product categories from the analysis where one of the models does not converge and/or shows near-perfect correlation between predictor and outcome, reducing the number of categories from 404 to 386.

Then, we use the estimated models to predict the difference each independent variable makes for the dependent variable, the product returns. That is, we predict the survival difference (i.e., the increase/decrease in non-returns) at the end of the entire return period due to a one-unit change in that variable during the entire return period.

Practically, we employ the implementation of R's rstmp2 package for estimation and prediction, including its implementation of the delta method to arrive at point predictions and standard errors for the predicted values (see Clements 2019; Royston and Lambert 2011).

Post-estimation cross-category heterogeneity analysis

Finally, to investigate (a) effect sizes across categories and (b) the influence of category-level characteristics, we use the survival estimates (Equation (6)) of the survival models as the dependent variable in weighted meta-regressions. We have two meta-regressions models. First, we seek an overall cross-category estimate of the effect size of each variable, i.e., the

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[2] Available working memory limits the data size to a maximum of about 1,000 purchases per category when estimating all categories together in one model, instead of 10,000-100,000 purchases per category using separate per-category estimation.

cross-category survival difference. For that, we regress an intercept on survival difference due to a change in each variable v_i:

$$\widehat{\boldsymbol{\Delta S_{v_i}}} = \mathbf{1}\alpha_{v_i} + \boldsymbol{\varepsilon}_{\boldsymbol{v_i}}\#(7)$$

for each variable v_i in model (I)-(III). For time-varying variables, we calculate the difference in survival due to a change from baseline $(0, 0, \ldots, 0)$, i.e., a vector of zeros for all days $t = [0,31]$, to $\boldsymbol{x}^* = (1, 1, \ldots, 1)$. Furthermore, we weigh each observation by its standard error.

Second, we assess the influence of category-level characteristics depending on prior customer behavior. For that, we extend the prior regression model by including category-level predictors:

$$\widehat{\boldsymbol{\Delta S_{d_i}}} = \mathbf{1}\alpha_{d_i} + \boldsymbol{z}_{\boldsymbol{d_i}}\boldsymbol{\beta}_{\boldsymbol{d_i}} + \boldsymbol{\varepsilon}_{\boldsymbol{d_i}}\#(8)$$

and estimate this model for variables d_i of the most encompassing survival model (III), i.e., the survival differences due to price reductions during or after purchase for light returners, heavy returners and customers who have not returned before. In sum, we therefore have six meta-regressions with this extended meta-regression model.

Results

We first present the main effects of price reductions during purchase and after purchase on the probability of keeping the product from model (I). Next, we present the effects of price reductions during purchase and post-purchase while accounting for the moderation effect of prior return behavior in general from model (II) and prior return behavior when differentiating between light and heavy returners from model (III). In the last section of the results, we show the effects of category-level moderators (Table Table 5).

Immediate effects of price reductions on returning

Table 2 presents the results for the effect of price reductions on the probability of keeping (i.e., not returning) a purchase in general. We find that whether or not a purchase is made during a price reduction has no significant different probability of being kept (-.1 percent points, n.s.), and that a price reduction after the purchase has a small positive effect on keeping the product (0.3 percent points, p < .001), providing no empirical evidence for H1a, H1b, or H2.

Table 2: The influence of price reduction on product returns, when not including recurring return behavior

Survival difference (no product return) due to…	ΔS	Std. err.	t value	p value	
Purchase during price reduction	-.001	.001	-1.426	.155	
Price reduction post-purchase	.003	.001	4.652	< .001	***
Prior returner	-.062	.004	-15.465	< .001	***
$\text{Gender}_{\text{male}}$	.008	.001	12.728	< .001	***
Age	.000	.000	2.182	.030	*
Purchase price	.000	.000	-6.905	< .001	***
Delivery fee	.006	.001	8.367	< .001	***
Basket size	-.002	.000	-15.950	< .001	***
Basket price	.000	.000	-12.233	< .001	***
Year_3	-.002	.001	-3.065	.002	**
Month_2	-.003	.001	-5.173	< .001	***
Month_3	-.003	.001	-4.843	< .001	***
Month_4	.003	.001	3.046	.002	**
Month_5	.002	.001	2.863	.004	**
Month_6	.000	.001	.237	.813	
Month_7	.009	.001	9.259	< .001	***
Month_8	.006	.001	7.309	< .001	***
Month_9	.003	.001	4.170	< .001	***
Month_{10}	-.001	.001	-1.318	.188	
Month_{11}	.003	.001	4.737	< .001	***
Month_{12}	.010	.001	13.128	< .001	***

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

While price reductions thus have no strong effect overall, we find that prior customer return behavior, in general, is influential: When a customer has returned before, the probability of keeping the current purchase is substantially decreased (6.2 percent points, p < .001). The remaining control variables generally show small influences on return behavior. Male customers and older customers have a higher chance of keeping the product. A delivery fee and the overall basket price increase the probability of keeping a product while product price and basket size decrease the chance of keeping the product slightly. When the purchase is in the second year of the estimation period, the probability of keeping the purchase is slightly lower. Months of the year can slightly increase or decrease the chance of keeping the product.

Influence of prior return behavior

Table 3 presents insights on the extent to which customers' prior return behavior with price reductions alters the effect of price reductions on the probability of keeping (i.e., not returning) a purchase. While a purchase made during a price reduction has a higher chance of being kept (2.2 percent points, $p < .001$) compared to a purchase not made during a price reduction, this only holds for customers that have not returned such a purchase in the past. Having returned a purchase made during a price reduction in the past, decreases the chance of keeping such a purchase (-3.4 percent points, $p < .001$) and thereby reverses the overall effect. Therefore, we find support for H1b and H3.

A similar picture emerges for price reductions post-purchase. A purchase with a post-purchases price reduction has a higher chance of being kept (2.2 percent points, $p < .001$), but prior returning of a purchase with a post-purchase price reduction lowers (-4.2 percent points, $p < .001$) and reverses the overall effect. Therefore, we find support for H4 but no support for H2. As before, returners of any prior purchase have a lower probability of keeping the current purchase (5.9 percent points, $p < .001$).

Regarding other control variables, the effects are similar to the previous model. Delivery fee, male gender and age significantly increase the chance of keeping the purchase while product price, basket size, basket price and purchasing in the second year of the estimation period significantly decrease the chance of keeping the product. Months of the year, again, have small positive or negative effects.

Table 3: The influence of price reductions on product returns, when including recurring return behavior

Survival difference (no product return) due to…	ΔS	Std. err.	t value	p value	
Purchase during price reduction	.022	.001	20.673	< .001	***
Price reduction post-purchase	.022	.001	16.063	< .001	***
Prior returner with: purchase during price reduction[1]	-.034	.002	-21.557	< .001	***
Prior returner with: price reduction post-purchase[2]	-.042	.002	-21.362	< .001	***
Prior returner	-.059	.004	-15.908	< .001	***
$\text{Gender}_{\text{male}}$	.009	.001	12.867	< .001	***
Age	.000	.000	2.159	.031	*
Purchase price	.000	.000	-6.638	< .001	***
Delivery fee	.007	.001	8.862	< .001	***
Basket size	-.002	.000	-17.227	< .001	***
Basket price	.000	.000	-12.443	< .001	***
Year_3	-.001	.001	-2.275	.023	*
Month_2	-.003	.001	-4.336	< .001	***
Month_3	-.003	.001	-4.424	< .001	***
Month_4	.003	.001	3.454	< .001	***
Month_5	.003	.001	3.226	.001	**
Month_6	.001	.001	.789	.431	
Month_7	.010	.001	9.381	< .001	***
Month_8	.007	.001	7.435	< .001	***
Month_9	.003	.001	4.052	< .001	***
Month_{10}	-.001	.001	-1.332	.184	
Month_{11}	.003	.001	4.383	< .001	***
Month_{12}	.012	.001	14.039	< .001	***

Note: $*$ p<.05; $**$ p<.01; $***$ p<.001

[1]Purchase is during a price reduction and the customer has returned in such a case before

[2]Purchase is followed by a price reduction and the customer has returned in such a case before

Influence of prior return behavior for light and heavy returners

In a next step, we split the effect of prior returners into an effect of light prior returners (who have returned one or two purchases) and of heavy prior returners (who have returned more three or more purchases) to investigate which customers predominantly drive the previously observed effect. The results presented in Table 4 show that heavy returners drive the effect of prior returners while light returners are more similar to customers who have not returned before.

Table 4: The influence of price reductions on product returns; when differentiating between novice and experienced returners

Survival difference (no product return) due to…	ΔS	Std. err.	t value	p value	
Purchase during price reduction	.013	.001	16.976	< .001	***
Price reduction post-purchase	.014	.001	13.507	< .001	***
Light returner with: purchase during price reduction[1]	.013	.001	15.816	< .001	***
Light returner with: price reduction post-purchase[2]	.003	.001	4.180	< .001	***
Heavy returner with: purchase during price reduction[3]	-.023	.001	-19.016	< .001	***
Heavy returner with: price reduction post-purchase[4]	-.036	.002	-20.619	< .001	***
Light returner[5]	-.007	.001	-6.658	< .001	***
Heavy returner[6]	-.076	.004	-17.214	< .001	***
$\text{Gender}_{\text{male}}$	.005	.001	9.178	< .001	***
Age	.000	.000	3.548	< .001	***
Purchase price	.000	.000	-6.744	< .001	***
Delivery fee	.006	.001	8.285	< .001	***
Basket size	-.002	.000	-16.181	< .001	***
Basket price	.000	.000	-12.212	< .001	***
Year_3	.001	.001	1.487	.138	
Month_2	-.003	.001	-4.283	< .001	***
Month_3	-.002	.001	-3.579	< .001	***
Month_4	.004	.001	3.878	< .001	***
Month_5	.004	.001	3.927	< .001	***
Month_6	.002	.001	1.736	.083	
Month_7	.009	.001	8.709	< .001	***
Month_8	.006	.001	7.073	< .001	***
Month_9	.003	.001	4.099	< .001	***
Month_{10}	-.001	.001	-1.702	.090	
Month_{11}	.003	.001	4.147	< .001	***
Month_{12}	.011	.001	13.814	< .001	***

Note: ∗ p<.05; ∗∗ p<.01; ∗∗∗ p<.001

[1]Purchase is during a price reduction and the customer has returned in such a case before (1-2 times)
[2]Purchase is followed by a price reduction and the customer has returned in such a case before (1-2 times)
[3]Purchase is during a price reduction and the customer has returned in such a case before (3+ times)
[4]Purchase is followed by a price reduction and the customer has returned in such a case before (3+ times)
[5]Customer has returned before (1-2 times)
[6]Customer has returned before (3+ times)

In particular, a purchase made during a price reduction has a higher chance of being kept (1.3 percent points, $p < .001$) than a purchase not made during a price reduction. This effect is doubled for light returners (+1.3 percent points, $p < .001$) and reversed for heavy returners (-2.3 percent points, $p < .001$). Therefore, as before, we find supportive evidence for H1b and H3. Next, a purchase with a price reduction post-purchase has a higher chance of being kept (1.4 percent points, $p < .001$) than a purchase without a price reduction post-purchase. Again, this effect is slightly strengthened for light returners (+0.3 percent points, $p < .001$) and reversed for heavy returners (-3.6 percent points, $p < .001$). Therefore, as before, we find supportive evidence for H4 and no support for H2.

Light returners of any prior purchase have a slightly lower chance of keeping the purchase (-0.7 percent points, $p < .001$) while heavy returners have a much lower chance of keeping the purchase (-7.6 percent points, $p < .001$), compared to customers who did not return anything so far. The remaining control variables have very similar effects to the previous two models.

Category-level heterogeneity

In a final analysis step, we examine whether and how the effect of price reductions, during and after the purchase, on keeping (i.e., not-returning) a product differs across product categories. We also investigate the respective effects for light and heavy returners, as before.

Overall, effect strength varies substantially across categories (Figure 2). The effects of having purchased during a price reduction and of price reductions post-purchase are generally positive, i.e., increase the chance of keeping the purchase, in almost all categories (Figure 2, first row). These effects do not show the whole picture, i.e., the effects of price reductions for heavy vs. light returners. While being a heavy returner generally leads to negative effects, i.e., decreases the chance of keeping the purchase, in practically all categories (Figure 2, third row), light returners have more mixed and less significant effects (Figure 2, second row).

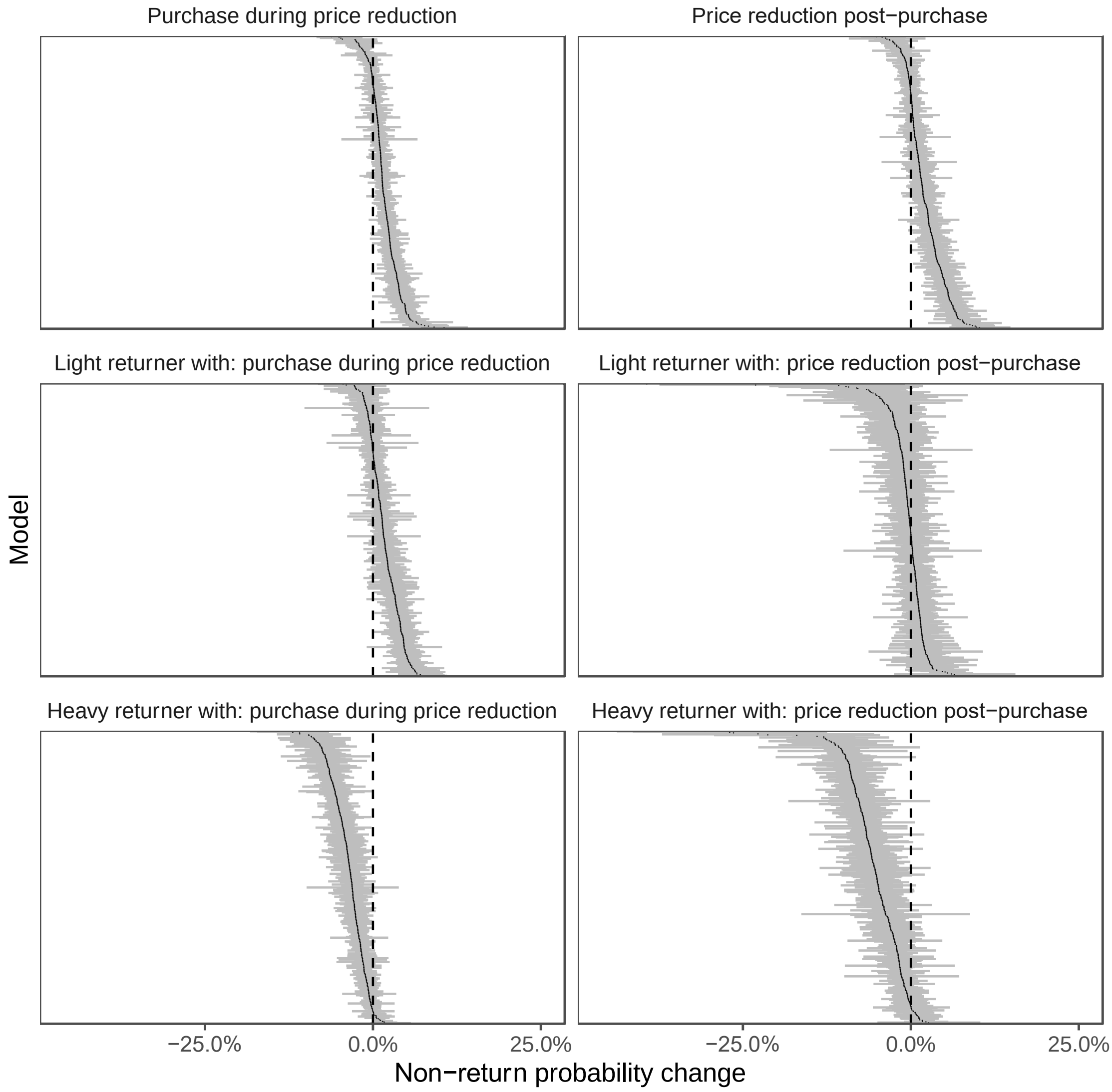

Figure 2: Cross-category variation in change of predicted non-return probability for purchases during price reduction, price reductions post-purchase in general, for light returners, and for heavy returners

Next, we relate the cross-category differences to the product characteristics, using equation (8). Table shows whether and how product category characteristics have a significant influence on the observed cross-category variation. Overall, product category characteristics in all cases explain a significant amount of the variance with highest explanatory power for heavy returners (R2 = .397 and .392), least for light returners (R2 = .315 and .081), and price reductions in general in between (R2 = .168 and .354).

Across all customers, we observe that the baseline effect of a purchase being made during a price reduction is higher for utilitarian categories and lower for search good categories. The baseline effect of a price reduction post-purchase, in turn, is higher for categories that contain more articles and lower for durable, gift, search good and utilitarian categories.

For light returners of purchases made during a price reduction, the baseline effect is higher for categories that contain more articles and lower for bulky, gift, hedonic and search good categories. Light returners of purchases with price reductions post-purchase, in turn, show a higher baseline effect for durable, gift and utilitarian categories and a lower one for search good categories.

For heavy returners of purchases made during a price reduction, the baseline effect is higher for search good categories and lower for hedonic and seasonal categories. Heavy returners of purchases with price reductions post-purchase, in turn, show a higher baseline effect for gift, search good and utilitarian categories and a lower one for categories that contain more articles.

Summarizing the effects, some product category characteristics clearly stand out as most influential. Search good categories always show a significantly weaker effect of price reductions on returning. As expected, for gift and utilitarian categories, the effect of post-purchase price reductions and being a heavy returner of purchases with post-purchase price reductions is significantly weaker. The remainder of the category characteristics has a more limited or even no impact on the estimated effect sizes.

Table 5: Category-level moderators of effects of dependent variable on returns

Coefficient	Purchase during price reduction		Price reduction post-purchase		Light returner with: purchase during price reduction		Light returner with: price reduction post-purchase		Heavy returner with: purchase during price reduction		Heavy returner with: price reduction post-purchase	
Constant	.018	***	.031	***	.026	***	.001		-.040	***	-.060	***
Bulky	-.004		-.003		-.009	**	.000		.003		.005	
Durable	-.001		-.009	***	-.003		.008	**	-.002		-.003	
Gift	.001		-.011	***	-.008	**	.007	*	.003		.018	**
Hedonic	.004		-.003		-.004	*	-.003		-.005	*	-.002	
Search good	-.011	***	-.009	**	-.009	***	-.007	**	.027	***	.032	***
Seasonal	.004		-.002		.001		.000		-.009	*	-.002	
Utilitarian	.004	*	-.007	**	-.003		.006	**	.002		.010	**
Average price	.001		-.001		.000		-.002		.001		.000	
Number of articles	.002		.006	***	.004	***	-.001		-.002		-.005	**
Number of brands	.000		-.002		.000		.001		.001		.000	
Observations	386		386		386		386		386		386	
R^2	.168		.354		.315		.081		.397		.392	
F statistic (df=10; 375)	7.562	***	20.537	***	17.234	***	3.324	***	24.639	***	24.216	***

Note: ∗ p<.05; ∗∗ p<.01; ∗∗∗ p<.001

Discussion

Summary of findings

In this paper, we studied whether online purchases are more or less likely to be returned if the product price is reduced (a) during purchase or (b) post-purchase, i.e., during the return period. We account for possible learning effects by customers – i.e., whether the effect of these price reductions is different if customers have returned an earlier purchase with a respective price reduction. In addition, we studied whether and how the effects vary across product categories. Table 6 presents an overview of our findings.

Table 6: Overview of the main findings

Findings:		
- Customers are *more* likely to return a product that is purchased during a price reduction.	**not supported**	(H1a)
- Customers are *less* likely to return a product that is purchased during a price reduction.	**partially supported**	(H1b)
- Customers are more likely to return a product with a post-purchase price reduction.	**not supported**	(H2)
- Customers are more likely to return a product that is purchased during a price reduction the more they have returned products purchased during a price reduction in the past.	**supported**	(H3)
- Customers are more likely to return a product with a post-purchase price reduction the more they have returned products with a post-purchase price reduction in the past.	**supported**	(H4)
Empirical findings on product category differences:		
- The direction of the effect is generally consistent across categories.		
- The strength of the effect varies across categories and tends to be weaker for search goods, utilitarian and gift categories.		

We find that price reductions during and after purchase can both lead to 2.2 percent points less returns, compared to when there is no price reduction – for customers that did *not* return a purchase with the respective price reduction in the past. On the other hand, when customers *did* return a purchase with the respective price reduction in the past, the effect of price reductions during and after purchase on returns is decreased by 3.4 and 4.2 percent points, respectively, and therefore reversed. Consequently, for customers that *did* return a purchase with the respective price reduction in the past, both price reductions during and after purchase lead to more returns, compared to when there is no price reduction. We find that the effects are predominantly driven by heavy returners, i.e., customers who have returned more than two purchases with the respective price reduction. In sum, price reductions can foster or prevent returns, with effect strength and directionality being affected by customers recurrent reaction to such promotions. On the other hand, whether a price reduction takes place during or after purchase has little influence on its effect on returning. Furthermore, we find that the effects are present in almost all sorts of product categories, with the strength of the effect tends to be weaker for search goods, utilitarian, and gift categories.

The findings are partly in line with what we predicted. A price reduction during purchase lowers the price that customers pay and a lower price leads to lower expectations of the product (Grewal 1995). With lower expectations, customers are more likely to find the purchase satisfying and therefore keep the product instead of return it. This is in line with what Petersen and Kumar (2009) found and partly in line with our prediction.

Contrary to our expectations, however, price reductions post-purchase lower returns. We theorized that seeing price reductions post-purchase could further regret in customers (Simonson 1992; Tsiros and Hardesty 2010; Zeelenberg and Pieters 2007) and consequently incentivize returns. It might be, however, that the advertising coupled with price promotions instead increases the perceived value of the product, thus decreasing regret and therefore also returns. Unfortunately, we do not observe in our data whether a price reduction is accompanied by communication and how visible the promotion is to the customer, and therefore cannot control for it. Another possibility is that customers are still able to profit from post-purchase price reductions, e.g., by calling the customer service center of the retailer and trying to carve out an exception to still get a price reduction after the purchase thereby having the price difference refunded without actually returning the product.

In accordance to our predictions, the effects of price reductions depend on prior customer return behavior in the context of such reductions. For purchases that were made during a price reduction – by customers that returned such purchases before – returns are higher than for purchases that were not made during a price reduction. This is in line with the theoretical argument that such price reductions are prone to cause impulse purchases for some customers, depending on personality traits (Sharma, Sivakumaran, and Marshall 2010), which are returned more (Kacen, Hess, and Walker 2012; Xu and Huang 2014). Similarly, for purchases with post-purchase price reductions – by customers that returned such purchases before – returns are higher than for purchases without a post-purchase price reduction. This effect supports the hypothesis that some customers recurrently respond to price reductions by returning – either due to being prone to regretting and therefore returning the purchase, or due to being strategic about returning (and re-purchasing) in order to save money. This line of reasoning is supported by prior research which indicates that customers, in general, habitually act or not act on promotions (Shah, Kumar, and Kim 2014).

Our study is the first encompassing investigation of the effects of price reductions on product returns. Our findings show that price reductions, regardless of their timing relative to the customer purchase, have an immediate decreasing effect on product returns. Customers, however, can get used to returning products that are reduced in price. Then, for these customers, price reductions do not prevent returns anymore, but foster them. As part of our study, we investigated more than 300 product categories and found that the effect is consistently present across almost all categories, which strongly supports the generalizability of our findings. In sum, our study contributes to research on price reductions by giving an account of their effect on product returns, and thereby support a more encompassing view of the advantages and disadvantages of price reductions.

Managerial implications

Online retailers on a nearly constant basis change prices for large parts of their assortment. Therefore, understanding the effects – and possibly unwanted side-effects – of price reductions is crucial. Our findings indicate that price reductions can both foster and lower product returns, depending on prior customer behavior. Customers who *have not* engaged in returning behavior before will return less as a consequence of purchasing during a price reduction or post-purchase price reductions. The effect is substantial, with the effect size varying depending on product category, being tendentially weakened for categories consisting of search goods, utilitarian products, and gifts. For customers who *have* returned in the past as a consequence of purchasing during a price reduction or post-purchase price reductions, the immediate effect is outweighed by a habitual effect and customers chance of returning a product will increase. Again, the effect depends on product category characteristics and, as before, tends to be weaker for categories consisting of search goods, utilitarian products, and gifts.

Our findings indicate that online retailers should take the influence of price reductions on product returns into account, when deciding on where and when to reduce prices. The crucial factor is customer past return behavior and it is important for retailers to assess which customers have a habit of returning due to price reductions. Since price reductions can both foster and lower returning depending on the sort of customer, retailers might want to promote personalized price reductions to customers, depending on their order history. Overall, price reductions have a wide range of effects and managers need to carefully apply them, based on retailer strategy and desired effects on sales, brand image and others. In order to prevent increased cost due to more product returns, the effect of price reductions on product returns should not be neglected, however.

Limitations and further research directions

Our study uses a large database from a generalist online retailer with tens of millions of purchases and returns in hundreds of product categories and assesses the empirical effect of price reductions. While our results show that price reductions can both foster and lower product returns, depending on the customer, the empirical nature of our study makes it difficult to assess the underlying mechanisms and intentions in the minds of the customers. A controlled lab experiment might help to investigate customer intentions and mental processes.

In addition, having only one retailer as data source means that company-specific aspects that might affect the effect of price reductions on product returns, such as return policy, are fixed for all purchases. A future study could include multiple retailers and study whether retailer-specific aspects play a role. In addition, having only one data source means that we cannot observe price reductions across retailers and their consequences on product returns. Although assortment difference usually limit customer switching across retailers (Lemon and Verhoef 2016), a future study could investigate whether such cross-firm effect exists.

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