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Credence Goods in Online Markets: An Empirical Analysis of Returns and Sales After Returns

Sebastian Feuß
RWTH Aachen University, feuss@time.rwth-aachen.de

Malte Brettel
RWTH Aachen University, brettel@time.rwth-aachen.de

CREDENCE GOODS IN ONLINE MARKETS: AN EMPIRICAL ANALYSIS OF RETURNS AND SALES AFTER RETURNS

Research paper

Sebastian Dominik Feuß, RWTH Aachen University, Germany, feuss@time.rwth-aachen.de

Malte Brettel, RWTH Aachen University, Germany, brettel@time.rwth-aachen.de

Abstract

While e-commerce sales continue to grow, product returns remain a key risk for online retailers' profitability. At the same time, credence goods such as sustainable products become increasingly important in retailing. This study aims to combine these two developments and empirically investigates the effect of credence goods on product returns and sales after returns in e-commerce. Furthermore, we assess how third-party assurances can help organizations to positively affect customer behavior and reduce product returns of credence goods. Our research is based on unique data from a large-scale online field experiment with 35,000 customers combined with data of more than one million past transactions of these customers. Surprisingly, the results reveal that credence goods are associated with lower product returns than experience goods. Adding a third-party certificate to the online product description helps to reduce product returns and increase sales after returns. We find that customer relationship strength and price consciousness act as boundary conditions for the certificate to reduce product returns. Our research contributes to signaling theory and extends IS literature on product uncertainty and returns to the field of credence goods. Furthermore, we provide relevant insights for e-commerce practitioners on how to manage sales and returns of credence goods.

Keywords: credence goods, product returns, customer characteristics, field experiment.

1 Introduction

E-commerce sales have strongly grown over the last years (U.S. Department of Commerce, 2017). In the 2017 Christmas holiday season online spending was higher than offline spending for the first time in history (Deloitte, 2017). While online sales continue to grow product returns remain a key risk of e-commerce retailers' profitability (Petersen and Kumar, 2009). Therefore, the information system and marketing literature has widely studied antecedents and consequences of product returns (e.g., Petersen and Kumar, 2009; De, Hu and Rahman, 2013). An important antecedent of product returns is product uncertainty (Hong and Pavlou, 2014). This is especially true for experience goods which are characterized by higher levels of product uncertainty than search goods (Mitra, Reiss and Capella, 1999; Hong and Pavlou, 2014). While the effect of experience and search goods on online product returns has already received some attention in the information system and e-commerce literature (e.g., Huang, Lurie and Mitra, 2009; Hong and Pavlou, 2014), there are almost no investigations on credence goods. Credence goods are defined as goods which carry some product attributes that can neither be evaluated before nor post purchase or consumption (Darby and Karni, 1973). Recently, credence goods such as organic food (Willer and Lernoud, 2016) or sustainable fashion (Very, 2016) are increasingly offered by offline retailers to benefit from higher margins (Bezawada and Pauwels, 2013) and to address rising environmental concerns of consumers (The Nielsen Company, 2015). At the same time, credence goods are generally associated with the highest product uncertainty (Mitra, Reiss and Capella, 1999) which is a key driver of product returns (Hong and Pavlou, 2014) and a key barrier to consumption in online markets

(Pavlou, Liang and Xue, 2007; Dimoka, Hong and Pavlou, 2012). Consequently, it is important to understand the effect of credence goods on product returns and sales after returns in e-commerce, a topic not yet comprehensively addressed by research.

The current literature on product returns and credence goods faces several limitations. First, it remains an open research question how to reduce product uncertainty in online markets leading to higher sales and lower returns (Dimoka, Hong and Pavlou, 2012; Hong and Pavlou, 2014). For credence goods third party certificates or third party labels (TPLs) have been found to work as an effective tool to reduce uncertainty and increase consumers' purchase intention in an offline context (Bauer, Heinrich and Schäfer, 2013; Brach, Walsh and Shaw, 2017). However, the role of TPLs on product returns and sales after returns of credence goods in e-commerce still needs to be understood. Second, research on how individual customer characteristics affect the relationship between product type and product returns is scarce. Since demographic variables are mostly non-significant in predicting consumer return behavior (Anderson, Hansen and Simester, 2009; Petersen and Kumar, 2009) research calls for the investigation of other customer characteristics (Kang and Johnson, 2009; Lee, 2015). Finally, there is only limited research leveraging actual transaction-based data when investigating product returns or customer characteristics (De, Hu and Rahman, 2013; Van Vaerenbergh *et al.*, 2014). Online retailers have completely new opportunities to track consumer shopping behavior (Hinz, Hann and Spann, 2011) but often do not use this information to target their marketing efforts accordingly (McAfee and Brynjolfsson, 2012). Therefore, it is important to understand how retailers could leverage this information to reduce returns and increase sales of credence goods. Our study seeks to address these shortcomings by answering the following three research questions: i) How do credence goods compared to experience goods affect product returns and sales after returns in e-commerce? ii) How do TPLs in the online product descriptions of credence goods affect product returns and sales after returns? iii) How could online retailers leverage information on customer characteristics when marketing credence goods?

We answer these research questions by developing and empirically testing a model which proposes that credence and experience goods differently affect product returns and sales after returns. These relationships are moderated by customers' relationship strength to the retailer and customers' price consciousness. Our research is based on a unique data set which was obtained in cooperation with a leading European fashion e-commerce retailer. The data set combines data on actual purchase and return behavior of more than 35,000 customers from a large scale online field experiment with data on more than one million past transactions to estimate several customer characteristics.

Our research contributes to the information system literature on product uncertainty (e.g., Dimoka, Hong and Pavlou, 2012; Kim and Krishnan, 2015), product type (e.g., Huang, Lurie and Mitra, 2009; Hong and Pavlou, 2014), and product returns (e.g., De, Hu and Rahman, 2013; Hong and Pavlou, 2014) in several ways. First, to the best of our knowledge, we are the first to empirically compare the causal effect of credence goods vs. experience goods on product returns and sales after returns in e-commerce. Thereby, we extend past information system literature to the field of credence goods. Second, we extend existing research on the importance of credible signals when selling credence goods offline to online product returns and sales after returns. Third, we answer several research calls (Kang and Johnson, 2009; Lee, 2015) by investigating how different customer characteristics affect product returns in e-commerce. Finally, we advance existing research on product returns by leveraging a unique data set based on actual transaction data. Leveraging such data is uncommon and a key contribution (Petersen and Kumar, 2015) as many firms are not willing to share this sensitive data with external parties (Stock and Mulki, 2009).

2 Related research and theoretical development

2.1 Product uncertainty in online markets and the role of product type

Uncertainty has been widely discussed in the literature and has been identified as a major barrier to consumption in online markets (e.g., Pavlou, Liang and Xue, 2007; Dimoka, Hong and Pavlou, 2012). Based on the economics of information the relationship between producers and consumers is characterized by information asymmetries. In the marketplace, consumer must make decisions based on imperfect information which leads to uncertainty (Akerlof, 1970; Spence, 1973). Past literature differentiates between seller uncertainty and product uncertainty (Ghose, 2009). Seller uncertainty refers to consumers' inability to evaluate seller quality before the purchase and consumers' fear of opportunistic seller behavior after the purchase (e.g., not acknowledging product warranties) (Akerlof, 1970; Pavlou, Liang and Xue, 2007). Given the rich research on the topic (e.g., Ba and Pavlou, 2002; Pavlou, Liang and Xue, 2007) the issue of seller uncertainty has been mostly overcome, while product uncertainty remains an important consumer concern in e-commerce (Hong and Pavlou, 2014).

Over the last decade the information system literature has increasingly focused on product uncertainty (e.g., Dimoka, Hong and Pavlou, 2012; Luo, Ba and Zhang, 2012) which is defined as a "buyer's difficulty in evaluating the product (description uncertainty) and predicting how it will perform in the future (performance uncertainty)" (Dimoka, Hong and Pavlou, 2012, p. 397). In contrast to traditional markets, in e-commerce consumers' opportunities to evaluate products are limited because they cannot physically experience all aspects of a product prior to purchase (Dimoka, Hong and Pavlou, 2012). Therefore, consumers face higher uncertainty and as a consequence perceive higher risks in online markets than in traditional brick-and-mortar retail setting (Biswas and Biswas, 2004).

In online as well as offline markets the level of product uncertainty and its consequences depend on the type of product or service (Mitra, Reiss and Capella, 1999; Hong and Pavlou, 2014). Products can be differentiated in search, experience, and credence goods depending on the characteristics of its key attributes (Nelson, 1970, 1974; Darby and Karni, 1973). While consumers can evaluate the key attributes of search goods before purchase, they can only assess the key attributes of experience goods (e.g., fit and feel of clothing purchased online) post purchase or consumption (Nelson, 1970, 1974). Credence goods are considered so because their dominant attributes cannot be assessed by consumers – neither prior nor post purchase (Darby and Karni, 1973). Examples of credence goods include organic food products (Ngobo, 2011), green electricity (Dulleck, Kerschbamer and Sutter, 2011), and insurances (Hsieh, Chiu and Chiang, 2005). Previous research shows that consumers' uncertainty and perceived risk increases along a continuum from search to experience to credence goods (Mitra, Reiss and Capella, 1999). In an online environment, Hong and Pavlou (2014) confirm that due to the imperfect information at point of sale experience goods are characterized by a higher degree of product uncertainty than search goods. The differences in uncertainty between product types substantially affect consumers' online shopping behavior (Kim and Krishnan, 2015). In an offline context Brach, Walsh, and Shaw (2017) show that sustainable products as one example of credence goods are associated with higher perceived risk and lower purchase intention than other products (i.e., search or experience products).

2.2 Product returns in e-commerce

Product returns are a highly relevant topic in e-commerce and have been found to significantly reduce retailer's profitability (Petersen and Kumar, 2009). Previous academic and practical investigations show that the majority of products are not returned due to defects but rather because the products do not fulfill customer expectations (Accenture, 2008; Lee, 2015). Due to the high uncertainty at point of sale online environments are characterized by a two stage decision process: The decision to order online based on imperfect information and the decision to keep the item after physically evaluating the product (Wood, 2001). Online consumers often postpone their final product evaluation until they can physically assess the product after receipt resulting in high levels of product returns in e-commerce (Wood, 2001). Expectation-confirmation theory implies that consumers' product assessment after receipt results from the actual product performance after delivery and whether consumers' expectations formed at point of sale were confirmed or disconfirmed (Oliver, 1977, 1980; Bhattacherjee, 2001). With higher uncertainty at point of sale it is more likely that consumers' expectations are not met after physically evaluating the product. Thus, product uncertainty is positively related to product returns (Hong and Pavlou, 2014). Hong and Pavlou (2014) show empirically that experience goods are associated with higher returns than search goods and that this effect is mediated by the level of product uncertainty. Since credence goods are associated with the highest level of consumer uncertainty at point of sale (Mitra, Reiss and Capella, 1999; Pan and Chiou, 2011), we expect an even stronger effect of credence goods on product returns and formulate the following hypotheses:

H1: Credence goods are associated with higher product returns than experience goods.

H2: Credence goods are associated with lower sales after returns than experience goods.

2.3 Online retailers' strategies to manage product sales and returns

There is a large body of marketing research investigating how online retailers could effectively manage product sales and returns. Many of the existing papers focus on how different return policies affect consumer behavior (e.g., Wood, 2001) and overall firm profitability (e.g., Anderson, Hansen and Simester, 2009). Finding the optimal return policy presents a significant challenge for online retailers. On the one hand, lenient return policies lead to higher product returns which are associated with high operational and financial cost reducing retailer profitability (Accenture, 2008; Ofek, Katona and Sarvary, 2011). On the other hand, lenient return policies decrease online consumers' perceived risk (Wood, 2001; Petersen and Kumar, 2009) leading to higher sales (Petersen and Kumar, 2015), higher levels of customer trust, and to stronger behavioral and attitudinal loyalty (Morgan and Hunt, 1994).

Therefore, researchers and practitioners investigate other ways to manage product sales and returns than strict return policies (Anderson, Hansen and Simester, 2009). In particular, mitigating product uncertainty through IT-enabled solutions is at the core of current research because it is expected to benefit both – sales and returns (Dimoka, Hong and Pavlou, 2012). In the context of an online marketplace for used cars Dimoka, Hong, and Pavlou (2012) find that helpful online product description and third-party product assurances are negatively related to product uncertainty. Other authors find that product pictures are especially helpful to reduce product uncertainty for experience goods, while product information provided from independent third parties is more effective for search goods (Weathers, Sharma and Wood, 2007). Recently, Lohse, Kemper, and Brettel (2017) show that online customer reviews are an effective tool reducing product returns and increasing sales after returns.

Investigations on how to reduce product uncertainty for credence goods are rather scarce. Previous research finds that presenting more information to the consumer is negatively related to consumers' perceived risk when purchasing legal services (Crocker, 1986). In the context of sustainable products especially TPLs are widely admitted to reduce consumers' perceived risk and positively affect consumer purchase behavior (e.g., Bauer, Heinrich and Schäfer, 2013; Brach, Walsh and Shaw, 2017). Following signaling theory (Spence, 1973) TPLs work as an effective signal sent by the producer to the consumer and decrease information asymmetries (Atkinson and Rosenthal, 2014). If TPLs work as an effective signal reducing product uncertainty of credence goods in an offline context (Brach, Walsh and Shaw, 2017), they are likely to have an even stronger effect in an online environment (Biswas and Biswas, 2004). Furthermore, given existing information system research that shows that third party product assurances negatively affect product uncertainty (Dimoka, Hong and Pavlou, 2012) and that product uncertainty is positively related to product returns (Hong and Pavlou, 2014), TPLs will most likely reduce product returns of credence goods. It is especially relevant to understand if the uncertainty reduction is sufficiently strong to lower returns of certified credence goods below the level of experience goods.

H3: Credence goods with a TPL are associated with lower product returns than experience goods.

H4: Credence goods with a TPL are associated with higher sales after returns than experience goods.

2.4 The moderating role of customer characteristics

Customer characteristics significantly affect purchase and return behavior (Petersen and Kumar, 2009). Since demographic variables are mostly non-significant in predicting consumer return behavior (Anderson, Hansen and Simester, 2009; Petersen and Kumar, 2009) research calls for the investigation of other individual characteristics in the context of product returns (Lee, 2015). The customer-firm relationship is one important characteristic frequently studied in marketing and consumer research (Aaker, Fournier and Brasel, 2004). Most relationship research agrees that good customer relationships are a competitive advantage (Grégoire and Fisher, 2006). Good customer relationships are positively associated with customer retention (Sheth and Parvatiyar, 1995), purchase behavior (Hewett and Krasnikov, 2016), and customer equity (Zhang *et al.*, 2016). To measure relationship strength researchers often leverage data on the transactional history between a customer and the firm (e.g., Hess, Ganesan and

Klein, 2003; Pick *et al.*, 2015). The transactional history of a customer is also relevant in the context of product uncertainty. Erdem and Keane (1996) show that previous transactions with a producer reduce uncertainty for the consumer. Arguing with learning theory Kim and Krishnan (2015) find that with an increasing number of past purchases consumer can better estimate product quality of an online retailer. This leads to more purchases of products with a high degree of product uncertainty. Other authors confirm that especially when evaluating credence goods consumer rely on previous experiences with the retailer (Mazaheri, Richard and Laroche, 2012). This is because repeated transactions between customers and retailers increase retailer credibility (Doney and Cannon, 1997). Based on signaling theory credibility is an important prerequisite for a TPL to reduce product uncertainty and affect consumer behavior (Erdem and Swait, 1998; Balasubramanian and Cole, 2002). For sustainable products Brach, Walsh, and Shaw (2017) find that the perceived credibility of a TPL is a boundary condition for the positive effect between TPLs and consumers' risk perception. Based on the effect of good customer-firm relationships on credibility and the importance of credibility to make TPLs work as an effective signal we formulate the following hypotheses:

H5: The negative effect of credence goods with a TPL (vs. experience goods) on product returns is moderated (reinforced) by customer relationship strength.

H6: The positive effect of credence goods with a TPL (vs. experience goods) on sales after returns is moderated (reinforced) by customer relationship strength.

Another important characteristic in the consumer research and marketing literature is consumers' price consciousness (e.g., Lichtenstein, Ridgway and Netemeyer, 1993; Juhl, Fenger and Thøgersen, 2017). Price consciousness is defined as the importance of price in the consumer's product evaluation process (Erdem, Swait and Louviere, 2002) and has been found to be negatively related to price acceptability (Lichtenstein, Bloch and Black, 1988). Consequently, price-conscious consumers perceive a certain price as higher and less acceptable than less price-conscious consumers and may thus react differently (Monroe, 1973; Jacoby and Olson, 1976; Berkowitz and Walton, 1980). The return literature further shows that price is positively associated with product returns. As prices increase customers assign a higher value to the product at point of sale which makes it more likely that their post-purchase evaluation deviates from their expectations resulting in a product return (Petersen and Kumar, 2009; De, Hu and Rahman, 2013). Since price-conscious consumer perceive a certain objective price as higher it can be expected that also price consciousness is positively related to product returns.

Previous literature shows that price-conscious consumers mainly focus on price as the key purchase decision criterion (Lichtenstein, Ridgway and Netemeyer, 1993). This is expected to have implications on the effectiveness of quality signals such as TPLs. As price is used as the main decision criterion in the purchase decision-making process, other purchase criteria such as TPLs may be neglected. Empirically, Bernard, Bertrandias, and Elgaaied-Gambier (2015) show that for price-conscious consumers information on the environmental harmfulness of products are less important for their purchase decision. This is in line with recent research finding lower adoption rates of organic products for highly price-sensitive households (Juhl, Fenger and Thøgersen, 2017). Other authors derive similar results in the context of product returns. Minnema et al. (2016) show that the positive effect of online customer reviews on product returns is weaker for more expensive products. In line with previous research on product returns and price consciousness we argue that the signaling role of TPLs is weaker for price-conscious consumers and formulate the following hypotheses:

H7: The negative effect of credence goods presented with a TPL (vs. experience goods) on product returns is moderated (attenuated) by customers' price consciousness.

H8: The positive effect of credence goods presented with a TPL (vs. experience goods) on sales after returns is moderated (attenuated) by customers' price consciousness.

3 Research Methodology

3.1 Research context and data collection

The data for this research was obtained in cooperation with a large European online retailer selling shoes and clothes to more than 20 million customers. Investigating product returns and sales after returns in the online fashion industry is well established in research (e.g., De, Hu and Rahman, 2013; Lohse, Kemper and Brettel, 2017) because fashion e-commerce is facing a significant amount of product returns for reasons of taste and fit (Ofek, Katona and Sarvary, 2011). Furthermore, apparel products can be differentiated in conventional apparel products which are experience goods if sold online (Kim and Krishnan, 2015), and sustainable products which are credence goods (Ngobo, 2011; Brach, Walsh and Shaw, 2017). This allows us a comparison between credence and experience products within the same industry. In this study we use to the term sustainable products to refer to all products that claim to be produced under consideration of social and/or environmental aspects (Luchs *et al.*, 2010).

The cooperation allows us to leverage a unique data set consisting of (1) data on actual purchase behavior of more than 35,000 consumers from a large scale online field experiment, (2) data on returns of more than 6,000 products bought during the experiment, and (3) data on more than one million past transactions to estimate several customer characteristics. We conducted the randomized online field experiment on the retailer's website during January and February 2017. Similar to other online fashion stores the website provides consumers with different navigation options to find the right product such as browsing through multiple overview pages or directly searching for products. Once selecting a specific product, the consumer is directed to the product page. On each product page there is a product picture and additional information on price, size, and material available to the consumer. By clicking on the add-to-cart button next to the product picture the consumer is directed to the checkout process where the final purchase takes place. In our experimental design we manipulated consumers' perception of the product type by displaying different information on the product page of more than 700 clothing items from the kids category. For each product we designed three different treatment groups:

- Control condition ("Experience good"): In this group the product page did not contain any credence information cues. Therefore, consumers allocated to this condition perceive the product as a regular online fashion item which can be experienced post-delivery.
- Treatment 1 ("Credence good"): In this condition the product page includes a green banner "Sustainable" in the upper part of the product picture, which ensures high visibility. Due to the credence claim "Sustainable" consumers allocated to this group perceive the item more as a credence good than in the control condition.
- Treatment 2 ("Credence good with TPL"): In addition to the "Sustainable" banner a TPL verifying environmental friendliness of the fashion product was placed below the product picture. Therefore, while still perceiving the product more as a credence good than in the control condition, consumers in this condition were also exposed to a strong signaling cue reducing product uncertainty.

For legal reason no falsified information has been displayed to the consumer as all products included in the experiment fulfil the sustainability claims in treatment group two and three. We only exclude this information from the control group. We included all sustainable kids products the retailer was offering in January 2017 into our experiment. The resulting set of manipulated products is diverse including 22 accessories products, 91 shoe products, and 647 apparel products. Besides the credence product information all functional and visual attributes were identical for each product across the three treatment groups. Once a consumer was visiting the product page of a manipulated product the consumer was part of our experiment and randomly allocated to one of the three treatment groups based on individual cookie-level data. Consumers had no possibility to explicitly search for sustainable products on the retailer's website as searchability of the experimental products was disabled during the time of the experiment. Over the course of the experiment each participant stayed within the same treatment group. The random allocation of consumers to treatment groups allows us to estimate the causal effect of the product type on consumer behavior (Sahni, 2016).

The online retailer offers its customers free returns and one hundred percent reimbursement up to three months after the purchase. After the three-month period, no more product returns for reasons of taste and fit are accepted by the retailer. To ensure capturing all product returns related to purchases during our experiment we collected data on product returns six month after the end of our experiment based on unique order identifiers. Due to the lenient return policies and the well-established market position of the retailer we assume that seller uncertainty does not significantly affect purchase decisions in our experimental setup. Our study focuses on consumers who were logged-in into their customer account during the experiment. These customers can be uniquely identified through a customer identifier which gives us access to their full history of past transactions with the retailer.

We group all product pages browsed by one customer within two hours into a session. Like other authors we rank all sessions by the number of pages browsed and exclude the top 0.5% of all sessions from our final sample to account for outliers caused by crawlers or test buyers (Hoban and Bucklin, 2015; Sahni, 2016). Our final sample contains 102,028 product page visits from 36,926 unique customers. The page visits are almost equally distributed on the three treatment groups (Control: 33.45% of observations, Treatment 1: 33.31% of observations, Treatment 2: 33.24% of observations) and resulted in 6,137 purchases, 1,802 product returns, and 4,253 sales after returns. Table 1 summarizes some of the key statistics per treatment group. Following existing studies (Petersen and Kumar, 2009; De, Hu and Rahman, 2013) we include only page visits resulting in a purchase for our analyses on product returns, while we include the full sample for our analyses on sales after returns.

Treatment group	**Number of product page visits**	**Product page visits, %**	**Number of sales**	**Number of returns**	**Number of sales after returns**
Control	34,125	33.45%	2,015	649	1,331
Treatment 1	33,919	33.31%	2,007	577	1,425
Treatment 2	33,984	33.24%	2,115	576	1,497
Total	102,028		6,137	1,802	4,253

Table 1. Descriptive statistics per treatment group.

3.2 Key variables

For each visit on a product page we observe on the individual level if the visit results in a purchase and/or in a return of the product. Based on this data we define our first dependent variable *product returns* in line with previous research as a binary variable which takes the value of one if a customer purchases and returns a product and the value of zero if a customer purchases but does not return a product (De, Hu and Rahman, 2013). Similarly, we define our second dependent variable *sales after returns* as a binary variable which equals one if a customer purchases but does not return a product following a visit on the product page. The variable takes the value zero if the consumer does not purchase the product or if the customer returns the product. We define our independent variable *product type* according to the three experimental treatment groups described above. *Experience good* refers to all observations from consumers allocated to the control group. *Credence good* refers to all product page visits from consumers allocated to the first treatment condition. Finally, *credence good with TPL* refers to all observations from consumers allocated to the second treatment group. Labeling products as search, experience or credence goods based on their key attributes is in line with previous literature (Klein, 1998; Hong and Pavlou, 2014). For example, Hong and Pavlou (2014) categorize products as search or experience goods based on their relative assessment on a scale from 1 (pure search) to 7 (pure experience). Adding a credence attribute to the manipulated product as in treatment group one and two does not fully transform the fashion item into a credence product – however – we assume that adding the credence attribute makes the item at least more of a credence product than the regular fashion item displayed in the control condition.

In addition, we include two control variables in our model which are in line with other research on product returns. First, *price* refers to the list price of the product which has been found to affect product returns (De, Hu and Rahman, 2013). To control for the list price also allows us to isolate the effect of consumers' price consciousness in our moderation model. Second, *discount* is operationalized as the average percentage discount per product (Anderson, Hansen and Simester, 2009; De, Hu and Rahman, 2013). Due to the random allocation of consumers to treatment versions there are no additional control variables on the consumer level required (Sahni, 2016). Furthermore, especially demographic variables are found to be non-significant in predicting consumer return behavior (Anderson, Hansen and Simester, 2009; Petersen and Kumar, 2009).

Following leading publications in the customer relationship literature we operationalize the customer's *relationship strength* as the total number of orders the customer has placed with the retailer during the customer's lifetime (Hess, Ganesan and Klein, 2003; Pick *et al.*, 2015). In total, all customers included in our final sample account for more than one million past transactions. We estimate three different levels of the customer's *price-consciousness* based on the transaction history of each customer. Similar to Juhl et al. (2017) we compare the product price paid in every single past transaction of a customer to the average product price of the respective fashion category. Purchase prices of 40% or more below the average product price of a category are coded as -1, purchase prices of 60% or more above the average category price are coded as +1, and prices between as 0. For each customer we calculate an index of price-consciousness based on the arithmetic mean of all the estimated scores per customer. The highest quartile of all customers' price index is categorized as low price-conscious, the lowest quartile as highly price-conscious, and the remaining 50% as intermediate price-conscious. Table 2 presents descriptive statistics for all continuous variables.

Variable	**Mean**	**SD**
Price (Euro)	29.85	22.00
Discount (Relative price discount)	0.24	0.19
Relationship strength (Number of orders)	38.04	55.83

Table 2. Descriptive statistics per continues variable.

3.3 Estimation approach

To estimate the effect of product type on returns and sales after returns based on the given data set we follow prior research and use binary logistic regression models (Sahni, 2016). To discuss H1-H4 we use product type as a predictor of product returns and sales after returns under consideration of different control variables. The dependent variable product returns is measured on the individual product purchase level, while sales after returns is measured on the individual product page view level. Model 1 and model 2 are formulated as:

(1) $P(Returns_{i,j}) = \frac{1}{1+exp(-(y))}$

(2) $P(SalesAftReturns_{i,j}) = \frac{1}{1+exp(-(y))}$

with $y = \beta_0 + \beta_1 * TG1_i + \beta_2 * TG2_i + \beta_3 * Price_j + \beta_4 * Discount_j + \varepsilon_{i,j}$

P (Returns) represents the probability of customer *i* returning product *j*. *P(SalesAftReturns)* represents the probability of customer *i* purchasing product *j* without returning it. *TG1* is a dummy variable indicating whether customer *i* was allocated to the credence product condition *(TG1 = 1)* or to the experience product condition *(TG1 = 0)*. Similarly, *TG2* indicates if the customer was allocated to the second treatment group (credence good with TPL) *(TG2 = 1)* or to the experience product condition *(TG2 = 0)*. *Price* refers to the first control variable representing the black price of product *j*. *Discount* is the second control variable indicating the average percentage discount per product *j*.

In order to analyze the moderating effect of relationship strength we modify model 1 and model 2 by adding the main effect of relationship strength of customer *i* (*RS*) and the corresponding interaction effect between product type and relationship strength to the model. In addition, we add price consciousness of customer *i* (*PC*) as a control variable. Furthermore, we focus on the comparison between credence goods certified with a TPL and experience goods and remove *TG1* from the models. This gives us model 3 and model 4:

(3) $P(Returns_{i,j}) = \frac{1}{1+exp(-(y))}$

(4) $P(SalesAftReturns_{i,j}) = \frac{1}{1+exp(-(y))}$

with $y = \beta_0 + \beta_1 * TG2_i + \beta_2 * RS_i + \beta_3 * RS_i * TG2_i + \beta_4 * PC_i + \beta_5 * Price_j + \beta_6 * Discount_j + \varepsilon_{i,j}$

In order to test the moderating effect of price consciousness we remove the interaction term of relationship strength and instead add the interaction effect between price consciousness and product type to model 3 and model 4. This gives us model 5 and model 6 which we do not present for simplicity reason. In all six models we correct for correlated behavior from the same customer by applying the Huber-White method to adjust the variance-covariance matrix of a fit from maximum likelihood (Huber, 1967; White, 1982). This correction is required because our data set contains multiple product page views from the same customer.

4 Empirical Results

4.1 Hypotheses testing

We use maximum-likelihood estimation in R (version 3.3.2) to run the logistic regression models. For interpretational reasons we standardize all values of the continuous variables. Table 3 displays the results.

Variable	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**	
	B	**(SE)**	**B**	**(SE)**	**B**	**(SE)**	**B**	**(SE)**	**B**	**(SE)**	**B**	**(SE)**
Constant	-.71***	(.06)	-3.27***	(.03)	-.78***	(.09)	-3.02***	(.05)	-.90***	(.10)	-2.99***	(.06)
Product type (Credence good)	-.24**	(.08)	.07	(.05)								
Product type (Credence good with TPL)	-.25**	(.09)	.12*	(.05)	-.26**	(.08)	.13**	(.05)	-.00	(.14)	.07	(.08)
Price	.59***	(.03)	-.44***	(.03)	.55***	(.04)	-.51***	(.04)	.54***	(.04)	-.51***	(.04)
Discount	-.26***	(.03)	-.03	(.02)	-.18***	(.05)	.01	(.02)	-.17***	(.05)	.08	(.02)
Relationship strength					.18**	(.07)	-.09 .	(.05)	.04	(.07)	-.00	(.06)
Price consciousness intermediate					.19 .	(.10)	-0.18**	(.06)	.37*	(.13)	-.21**	(.08)
Price consciousness high					-.14	(.14)	-.37***	(.07)	.10	(.18)	-.42***	(.09)
Credence good with TPL x Relationship strength					-.26*	(.11)	.13	(.09)				
Credence good with TPL x Price consciousness intermediate									-.37*	(.18)	.06	(.11)
Credence good with TPL x Price consciousness high									-.59*	(.26)	.10	(.13)
. = p < .1; * = p < .05; ** = p < .01; *** = p < .001. Note: For *product type* 'experience good' is selected as reference category. For *price consciousness* 'low' is selected as reference category. Standard errors are robust and clustered by customer.												

Table 3. Model results.

We first look at the main effects estimated in model 1 and model 2. In model 1 the two control variables price (.59, p < 0.001) and discount (-.26, p < 0.001) are significantly associated with product returns. In model 2 only price (-.44, p < .001) is significant while discount has no significant effect on sales after returns (-.03, p > .1). Surprisingly, against our first hypothesis there is a negative relationship between credence goods and product returns (-.24, p < .01). Furthermore, the relationship between credence goods and sales after returns is not significant (.07, p > .1). Hence, we need to reject H1 and H2. In line with H3 and H4 we find that adding a TPL to credence goods significantly improved performance compared to experience goods. Credence goods certified with a TPL are negatively associated with product returns (-.25, p < .01), and positively associated with sales after returns (.12, p < .05). The probability of a consumer returning a certified credence product is by 15.79% lower compared to an experience product (27.76% probability of return vs. 32.97% probability of return). Similarly, the probability of a purchase after returns increases by 12.55% from 3.65% to 4.10% for credence goods certified with a TPL compared to experience goods.

The results of model 3 reveal a significant interaction effect between relationship strength and product type (-.26, p < .05). The negative effect of credence goods certified with a TPL on product returns is substantially stronger for customers with a good relationship to the retailer. Thus, we can confirm H5. In contrast, the results of model 4 do not reveal a significant interaction effect between relationship strength and product type on sales after returns (.13, p > .1). Therefore, we reject H6. In order to understand the interaction effect between product type, relationship strength, and product returns in more detail we plot the relationship (figure 1). Relationship strength is displayed at one standard deviation greater than and less than the arithmetic mean of all standardized values. Figure 1 implies that for customers with a good relationship to the retailer credence goods certified with a TPL have lower product returns than experience goods. We conduct a simple slope test as proposed by other researchers (e.g., Cohen *et al.*, 2003; Dawson, 2014) and find that the difference between the product types is significant for high relationship strength (p < .001) but not for low relationship strength (p > .1).

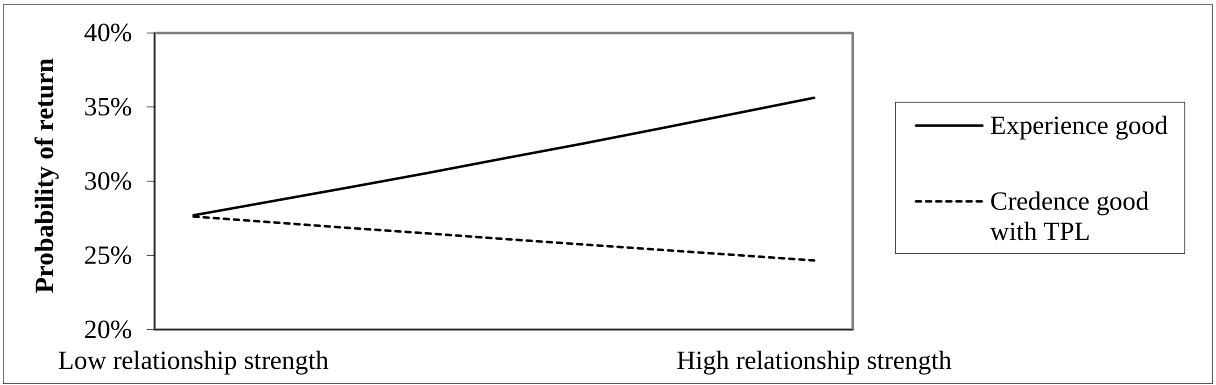

Figure 1. Interaction effect between relationship strength and product type.

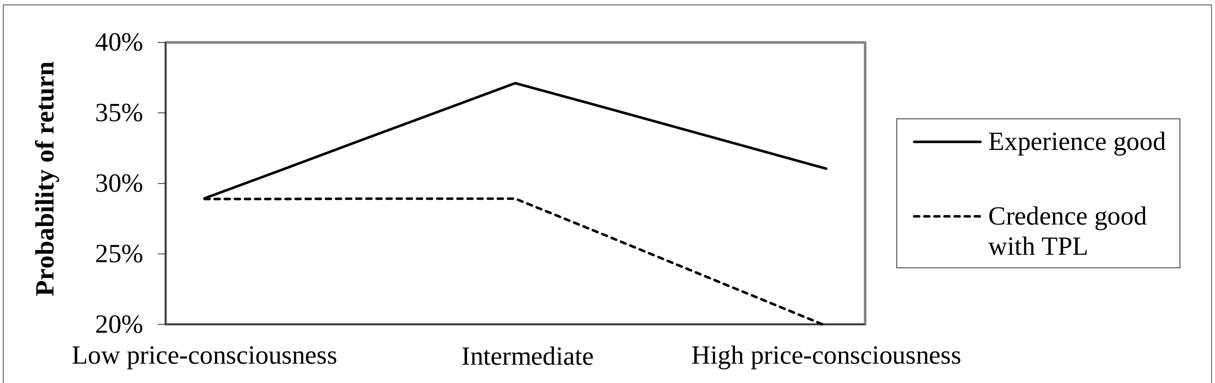

Figure 2. Interaction effect between price consciousness and product type.

Model 5 shows a significant interaction effect between customers' price consciousness and product type (low vs. intermediate price consciousness: -.37, p < .05; low vs. high price consciousness: -.59, p < .05).

However, against H7 price consciousness does not attenuate but reinforces the negative effect of credence goods certified with a TPL on product returns. Model 6 reveals no significant interaction effect between price consciousness and product type (low vs. intermediate price consciousness: .06, $p > .1$; low vs. high price consciousness: .10, $p > .1$). Thus, we need to reject H7 and H8. Figure 2 shows the relationship between price consciousness, product type and product returns in detail. The difference between experience goods and certified credence goods increases with higher consumers' price consciousness. The simple slope tests reveal a significantly different probability of product returns between the two product types for intermediate ($p < .01$) and highly ($p < .01$) price-conscious consumers. In contrast, there is no positive effect of certified credence goods on product returns for low price-conscious consumers ($p > .1$).

4.2 Robustness checks

We apply different robustness measures to ensure proper model fit and validity of results. First, we assess our models for multicollinearity. The pairwise correlation estimators of all variables included in our data set are below .25 and therefore far below the threshold of .8 (Kennedy, 2008). Furthermore, the variance inflation factors in all six models are between 1.0 and 3.8 suggesting that multicollinearity is not an issue with our estimation approach (Hair *et al.*, 2009). Second, we checked for outliers and influential cases. In all six models less than 5% of all observations have standardized residuals bigger than 1.96 or smaller than -1.96, and less than 1% of all observations have standardized residuals bigger than 2.58 or smaller than -2.58. Looking at cooks distance no influential observation were identified (Cook and Weisberg, 1982). In total, we assume that our models fit the observed data well. Third, to account for different numbers of experience attributes between product categories (e.g., shoes have more standard sizing and might, therefore, carry less experience attributes than clothing items due to fit issues) we control for the product category (shoes, apparel, accessories) in all six models. All results remain stable. Finally, instead of having different models per interaction effect we test the interaction effect between price consciousness and product type and between relationship strength and product type within one model for product returns and one model for sales after returns. The results remain stable with the only exceptions that the interaction effect between product type and intermediate price consciousness is only significant at the 10% confidence interval.

5 Discussion

5.1 Implications for theory

This study investigates the causal effects of credence and experience goods on product returns and sales after return. Our empirical results reveal that credence goods have lower product returns than experience goods but there is no significant difference in sales after returns. However, adding a TPL to the credence good not only leads to lower product returns but also results in higher sales after returns. The negative effect of certified credence goods on product returns holds only true for customers with a good relationship to the retailer or with intermediate or high price consciousness. Our research contributes to the information system literature on product uncertainty (e.g., Dimoka, Hong and Pavlou, 2012; Kim and Krishnan, 2015), product type (e.g., Huang, Lurie and Mitra, 2009; Hong and Pavlou, 2014), and product returns (e.g., De, Hu and Rahman, 2013; Hong and Pavlou, 2014) in several ways.

First, to the best of our knowledge, we are the first to empirically compare the causal effects of credence and experience goods on actual product returns and sales after returns in e-commerce. Thereby, we extend previous information system literature on the relationship between product type and online product returns (Hong and Pavlou, 2014) to the field of credence goods. Against our hypothesis we find that credence goods are associated with lower product returns than experience goods. This is surprising because credence goods are generally related to higher product uncertainty than experience goods (Mitra, Reiss and Capella, 1999) and product uncertainty is a key driver of product returns (Hong and Pavlou, 2014). This surprising result can potentially be explained by the specific nature of credence attributes. In contrast to experience attributes, credence attributes can never be evaluated by consumers – neither prior nor post purchase (Nelson, 1970, 1974; Darby and Karni, 1973). There is no additional information available to better evaluate credence attributes after product receipt and the difference between consumers' expectations and actual performance is likely to be smaller than for experience attributes. For example, once a consumer decides to purchase an organic cotton t-shirt the consumer believes in this credence claim (i.e., organic cotton). After delivery of the product the consumer does not receive any additional information regarding the credence attribute that could make the consumer question this belief. This is in contrast to experience attributes where consumers receive additional information after delivery which might make them change their purchase decision. Since experience goods are characterized by a higher share of experience attributes than credence goods, they have more product attributes for which the information pre- and post-delivery differs. Thus, following expectation-confirmation theory consumers' expectations formed at point of sale are more likely to be disconfirmed after delivery resulting in higher product returns for experience goods.

Second, we contribute to the literature on product uncertainty (Dimoka, Hong and Pavlou, 2012; Hong and Pavlou, 2014) and signaling theory (Darby and Karni, 1973) by showing that credence goods certified with a TPL are related to lower product returns and higher sales after returns than experience goods. This implies that TPLs work as an effective signal reducing product uncertainty of credence goods – even below the level of experience goods. Thereby, we confirm existing findings on the negative relationship between TPLs and product uncertainty (Dimoka, Hong and Pavlou, 2012) also for credence goods. Furthermore, we extend existing research on the importance of signals when selling credence goods (e.g., Atkinson and Rosenthal, 2014; Brach, Walsh and Shaw, 2017) to the field of e-commerce where product returns and sales after returns are even more important than initial sales.

Finally, we contribute to the ongoing debate on how customer characteristics affect perceived product uncertainty (Mazaheri, Richard and Laroche, 2012; Kim and Krishnan, 2015) and returns (Petersen and Kumar, 2009; Lee, 2015). Our results show that customers' price consciousness and their relationship to the retailer act as boundary conditions for a TPL to work as an effective signal reducing product uncertainty and lowering returns. As hypothesized relationship strength seems to increase customers' trust in the retailer which is a prerequisite for a TPL to work. Thus, relationship strength reinforces the negative effect of certified credence goods on product returns. Contradicting our hypothesis we find that price consciousness reinforces the relationship between certified credence goods and product returns. This is surprising because we were expecting that price dominates other signals as key purchase criterion for highly price-conscious consumers. However, our empirical results imply that TPLs work as an even stronger signal for highly price-conscious consumers. This may be because price-conscious consumers perceive a certain price as more expensive and thus related to higher risk (Sweeney, Soutar and Johnson, 1999). In high risk situations consumers may rely more on quality signals which increases the effect of TPLs for price-conscious consumers.

5.2 Practical implications

Our research provides valuable insights for e-commerce managers. First, our research shows that sustainable products as an example of credence goods are negatively related to product returns and do not significantly differ in sales after returns compared to experience goods. Thus, they are related to similar sales but lower operational and financial cost than experience goods (Accenture, 2008). This result encourages e-commerce managers to extend their assortment of sustainable products in order to address rising consumer demand (The Nielsen Company, 2015). Second, online retailers should consider offering more lenient return policies for sustainable products. While credence goods are negatively associated with product returns they are not positively associated with sales after return. This can be explained by lower initial sales due to the higher perceived risk at point of sale when purchasing credence goods (Brach, Walsh and Shaw, 2017). In line with literature on different return policies per product category (Anderson, Hansen and Simester, 2009), more lenient return policies decrease consumers' perceived risk leading to higher demand, while the risk of high product returns seems manageable for credence goods. Consequently, it might be optimal to offer different return policies for sustainable and conventional products. Since varying return policies depending on the type of product might be confusing for the customer as well as associated with increasing operational complexity, retailers should at least emphasize their lenient return policies when marketing sustainable products. Third, we encourage managers to use TPLs in the product descriptions when selling credence goods such as sustainable products, although the certification process is often costly and time-consuming (Brach, Walsh and Shaw, 2017). Investments into TPLs not only pay off from a sales perspective due to higher sales after returns but also decrease retailer's cost due to lower product returns. Fourth, our research underlines that the customer's level of price-consciousness and the customer's relationship strength to the retailer are important when managing returns and sales after returns of credence goods. Thus, online retailers should leverage available data to estimate these customer characteristics, build customer segments and adjust their sales and marketing approach accordingly. For example, they could target their marketing of sustainable products specifically to price-conscious consumers or customers who already have a good relationship with the retailer. Finally, for online retailers offering sustainable products it is even more important to invest into a good customer relationship. A good customer relationship pays off because it increases customer trust and significantly lowers product returns for sustainable products certified with TPLs. Therefore, online retailers should consider specific measures to strengthen their relationship with the sustainable target customer.

5.3 Limitations and future research

Our study faces some limitations that provide promising areas for further research. First, our study is based on data from one retailer only with a rather lenient return policy. The lenient return policy might be especially beneficial for products associated with high uncertainty such as credence goods. This limits the generalizability of our study. Future research is encouraged to replicate our results with different retailers and different return policies. Second, our field experiment is limited to only one example of a credence good. While, there are considerable benefits of analyzing the effect of sustainable fashion products on product returns, this is clearly one specific example limiting the generalizability of our results. Sustainable products are usually bought by consumers with high environmental concern (Pagiaslis and Krontalis, 2014). This might affect our results since consumers' environmental concern is in contrast to the high natural resources required (e.g., carbon emissions during transport) for online product returns (Saarijärvi, Sutinen and Harris, 2017). Therefore, the observed negative relationship between sustainable products as one example of credence goods and product returns might be partly affected by a consumer selection bias. Future research should extend our results to other examples of credence goods or control for additional customer characteristics such as environmental concern. Finally, within our online field experiment there is no possibility to conduct manipulation checks. In particular, we cannot ensure that the credence attribute added in the experimental conditions two and three makes consumers perceive the manipulated product as a credence good. Future research should account for this limitation by combining field data with customer survey data.

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