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Product returns in omni-channel retailing

Hirche, Christian

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Product Returns in Omni-channel Retailing

Christian F. Hirche

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Promotor

Prof. dr. T.H.A. Bijmolt

Copromotor

Dr. ir. M.J. Gijsenberg

Beoordelingscommissie

Prof. dr. J.E. Wieringa

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Christian F. Hirche, January 2022

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1

Introduction

The retailer landscape has undergone a transformation. E-commerce has become an important part of retailing. From 2010 to 2020, the number of consumers that have recently used e-commerce has doubled, from about one third to two thirds (Eurostat, 2021b, 2021c). Especially fashion products such as clothes and shoes are frequently ordered online among all age groups (Eurostat, 2021a). As part of this development, many former brick-and-mortar retailers have expanded to the Internet and created an online channel in addition to the pre-existing offline channel (Deloitte, 2018; Zaczekiewicz, 2018), and new online-first retailers have emerged (Statista, 2019). While online retailing thus continues to rise in importance, it has not supplanted offline retailing. Instead, customers expect retailers to be present across multiple channels (Bijmolt et al., 2019) and many retailers have embraced a so-called multi- or omni-channel business model (CB Insights, 2018; Thompson, 2017). With multi- or omni-channel retailing, customers are not limited to one channel such as a physical store of the retailer and they can interact with different channels for different steps of the customer journey. For instance, they may browse through the product assortment in a store and subsequently order a product online or, alternatively, search for products online and then visit a store to make the purchase.

1.1 Research on Online and Omni-channel Retailing Challenges

The developments sketched in the previous paragraph, i.e., the rise of omni-channel retailing as well as the growing extent of the online channel, create challenges for retailers. First, retailers need to coordinate between channels with regards to decisions about assortment and inventory, distribution and delivery, as well as the return process (Bijmolt et al., 2019). In addition, the existence of multiple channels might lead to interactions between channels where one channel influences visitors, sales, returns and, ultimately, profitability of another channel. Prior research has investigated the interplay between channels when adding a new channel with mixed results. Creating an offline channel can increase online purchases and returns (Avery et al., 2012; Pauwels & Neslin, 2015) but creating an online channel can under some circumstances increase (Li, 2021) or decrease offline purchases (van Nierop et al., 2011; Weltevreden, 2007). Prior research, however, generally investigates the effect of adding channels instead of coexisting channels, thereby possibly overstating short-term over long-term effects, which are important for retailers. In addition, it is an open question which differences between products might explain when channels have a positive or negative interplay.

Second, the online channel brings about its own challenges which rise in importance as online retailing continues to grow (Verhoef & Bijmolt, 2019). One of the

largest issues in online retailing is the high rate of product returns. Up to 45% of online fashion purchases in the US are returned, according to de Leeuw et al. (2016). Missing out on sales in addition to incurring costs for shipping and handling returns, product returns are a costly affair. They can make customer relationships unprofitable altogether and harm online retailer profitability (Asdecker, 2015; Minnema et al., 2018; Shah et al., 2012). In addition, both waste from unsalvageable returns as well as logistics for shipping returns back and forth between the retailer and the customer, causing extra traffic and greenhouse emissions, burden the environment (Edwards & McKinnon, 2009). A range of studies has investigated factors that influence returning in online retailing (see Minnema et al., 2018, for an overview). Often, factors that influence product returns also influence product purchases and therefore, many studies regard both aspects in tandem. Extant research on drivers of online purchases and returns can be grouped into research on (1) the availability of (retailer-provided and customer-generated) information before purchase, (2) shipping and return policy, (3) customer characteristics, and (4) product and marketing mix characteristics.

Information availability. Regarding the influence of the availability of retailer-provided or customer-generated information on online purchases and returns, previous studies show that more retailer-provided information (e.g., the ability to zoom into product images) leads to more realistic expectations about a product pre-purchase and therefore can lower purchases and returns (De et al., 2013). Too much information, however, may also increase expectations and returns (Shulman et al., 2015). Customer-generated information such as online customer reviews (Babić et al., 2015) mostly affect purchase decisions but overly positive reviews can also lead to overly high expectations and consequently high returns (Minnema et al., 2016).

Shipping and return policies. Regarding the influence of return policies, numerous studies show that monetary and effort leniency, i.e., making returning less expensive, e.g., by not asking restocking fee, or less effortful, e.g., by not asking for the original receipt, increases purchases but does not decrease returns (Bower & Maxham, 2012; Janakiraman & Ordóñez, 2012). Time and exchange leniency, i.e., a longer return deadline and offering cash refunds instead of store credit, does not influence purchases but decreases returns (Janakiraman & Ordóñez, 2012; Janakiraman et al., 2016). Scope leniency, i.e., allowing not only a subset of products to be returned, does not influence purchases but increases returns (Wood, 2001). Fewer studies have investigated the influence of the shipping policy on purchases and returns. A retailer's shipping policy prescribes whether customers have to pay a shipping fee – i.e., a mark-up on the price of an order, depending on the value and composition of an order. Retailers can employ a shipping policy that mandates free shipping or paid

shipping. When resorting to paid shipping, retailers usually employ either threshold-based free shipping, where orders surpassing a certain threshold value have free shipping, or fixed-fee shipping, where orders independently of size have a fixed shipping fee. Studies find that free shipping results in more frequent orders and more returns than fixed-fee shipping (Shehu et al., 2020) and more frequent orders than threshold-based free shipping (Lewis et al., 2006). So far, no study compares different paid shipping policies.

Customer characteristics. Regarding the influence of customer characteristics on returns, studies show few significant effects. Most importantly, previous experience of a customer with a certain product category decreases returning (Petersen & Kumar, 2009). Evidence for gender is mixed (Minnema et al., 2018). Other demographic variables, such as age, income, marital status, and education (Hong & Pavlou, 2014) have no significant influence on returning (Petersen & Kumar, 2009).

Product and marketing mix characteristics. Regarding product and marketing mix characteristics, product category is an important predictor of return probability, as different products in different categories are easier or harder to evaluate online before purchase (Hong & Pavlou, 2014). Furthermore, empirical findings by Petersen and Kumar (2009) suggest that products with a price reduction are purchased more and returned less. On the other hand, price reductions might also lead impulse purchases and subsequently more returns (Kacen et al., 2012; Xu & Huang, 2014) as well as more returns of previously purchased goods due to the opportunity to re-purchase the product at a lower price (Bandi et al., 2018). So far, no studies provide an integrative view of the overall effect of price reductions, i.e., combining the effect of price reductions for purchases that were made during the price reduction and the effect of price reductions for purchases that were made before the price reduction.

1.2 Overview of the Dissertation and Research Questions

Reviewing findings of extant research shows that several gaps and open questions still remain, both with regards to channel interactions among multiple channels as well as with regards to drivers of product returns in the online channel. The following three subsections introduce three research questions, which have not yet been answered by prior research, and will be investigated in the course of this dissertation.

1.2.1 Influence of Stores on Online Orders and Returns

For retailers that ponder embracing a multi-channel or omni-channel model, it is important to know advantages and disadvantages of employing multiple channels.

In particular, maintaining an offline channel comes with high costs, such as rent and wages, which are not present for online-only retailers. These additional costs must be outweighed by additional benefits. In addition to the revenue incurred by the offline channel itself, both channels might interact and, by that, the offline channel could change customer behavior in the online channel. In other words, the presence of physical stores could potentially harm or help the online business of retailers.

Prior research indicates that adding an online channel to an offline channel or, conversely, adding an offline channel to an online channel can have negative, neutral, and positive effects (e.g., Avery et al., 2012; Pauwels & Neslin, 2015; van Nierop et al., 2011). The study in chapter 2 aims (a) to explain diverging findings by integrating risk-related product characteristics into the analysis and (b) to provide a holistic view of the influence of the presence of an offline channel on online channel performance – by estimating its effect on online purchase frequency, online purchase volume, and online product returns. In sum, it investigates the following research question:

RQ1 What are the effects of physical stores on online channel customer behavior in terms of product purchases and returns?

The study consists of an empirical analysis of online customer behavior and physical store location data of a large retailer in the fashion industry. The empirical analysis makes use of a novel hierarchical Spatial Durbin Error Poisson model specification, which accounts for the spatial (i.e., two-dimensional) structure of store locations, customer locations, and the error term. In addition, perceived risk as a possible moderating effect is investigated. Finally, a simulation gives insights to what would happen when the number of physical stores would be reduced or increased.

1.2.2 Influence of the Shipping Policy on Online Orders and Returns

Online retailers have to choose a shipping policy which mandates if and when customers have to pay shipping fees. Depending on the shipping policy, a variety of factors (e.g., order size, product category) can determine the exact fee to pay for the customer. An important consideration for retailers is that the shipping fee structure likely influences product returns and product purchases (Lewis, 2006; Shehu et al., 2020), as shipping fees directly increase the price which customers have to pay. In order for the shipping policy to increase the profitability of the online retailer, it should increase the number of orders and decrease the number of returns (Minnema et al., 2018; Petersen & Kumar, 2015).

Chapter 3 contrasts two widely used paid shipping fee policies, fixed-fee shipping and threshold-based free shipping, and their influence on online purchases and returns. Fixed-fee shipping mandates fixed shipping fees, independent of the order

size, whereas threshold-based free shipping only mandates shipping fees for orders falling short of a certain value. The resulting difference in cost for the customer might motivate different purchase and return behavior. In addition, threshold-based free shipping might have the side-effect of motivating customers to purchase additional products to reach the free shipping threshold, so called filler-purchases, which might be returned more or less than the remaining purchases. Ultimately, these effects will make one shipping policy more profitable than the other. Comparing the effects of fixed-fee shipping and threshold-based free shipping on orders and returns and profitability, chapter 3 will address the following research question:

RQ2 What are the consequences of threshold-based free shipping in comparison to fixed-fee shipping on orders, returns, and profitability?

The chapter starts with a theoretical discussion, laying out how fixed-fee shipping and threshold-based free shipping might influence orders – aggregate sales as well as decomposed into order value and order count – and returns. Then, a regression analysis of a large dataset from a European online retailer, which changed its shipping policy from fixed-fee to threshold-based free shipping, empirically verifies the theoretical argument. The dataset contains 26.21 million orders by 3.81 million customers in a wide range of product categories. Finally, a simulation contrasts the practical profitability implications of both policies.

1.2.3 Influence of Price Reductions on Online Returns

Dynamic price changes are common in online retailing. That is, many retailers frequently adjust product prices based on e.g., demand changes, inventory level, and competitors' prices (Elmaghraby & Keskinocak, 2003; Fisher et al., 2018; Grewal, 2011; Grewal et al., 2010). When the retailer decreases the product price, one important positive effect is usually a boost in sales (Bijmolt et al., 2005; Gupta, 1988). However, price reductions might also affect the product return rate. Importantly, returns of two different sorts of purchases could be affected. First, the returns of purchases that are made during a price reduction – i.e., when the customer purchases a product at a reduced price – might change (Petersen & Kumar, 2009). Second, the returns of purchases that were made before a price reduction – i.e., when the customer has paid a higher purchase price than the post-purchase reduced price – and are still eligible to be returned, might change (Bandi et al., 2018). Chapter 4 examines the effect of both price reductions during or after the product purchase on returns. It thus addresses the following research question:

RQ3 Are products more (or less) likely to be returned (a) when they are purchased during a price reduction or (b) when there is a price reduction after purchase?

The chapter starts with a theoretical discussion of the reasons for which customers might be motivated to return more or less, leading to several hypotheses for when price reductions might increase or decrease returning. Then, a regression analysis of a large dataset from a European generalist online retailer of more than 80 million purchases in a wide range of product categories empirically tests the hypotheses. In addition, the extensive set of product categories allows to discern product category-specific and customer-specific effects.

1.3 Summary

In sum, while research both on channel interactions in multi-channel and omni-channel environments and on the challenge of product returns in the online channel is extensive, there are a number of important gaps with practical relevance for retailers. The first study of this dissertation (chapter 2) investigates the influence of pre-existing offline stores on purchase and return behavior in the online channel. In addition, it differentiates between purchases and returns of products with different levels of perceived risk. The second study of this dissertation (chapter 3) compares threshold-based free shipping with fixed-fee shipping in terms of orders, returns and profitability. In addition, it investigates whether threshold-based free shipping leads to so-called filler purchases with a higher or lower return rate. The third study of this dissertation (chapter 4) investigates whether a product is more (or less) likely to be returned due to a price reduction at the time of purchase or after purchase.

All chapters contain a separate introduction to their specific topic, subsequently present the theoretical background, employed methodology, model results, and conclude with a general discussion (see Table 1.1 for an overview). Each chapter can be read independently. All three chapters are empirical studies using large datasets of customer purchase and return data from large European retailers. Finally, the dissertation is concluded by a general discussion (chapter 5), laying out the findings of each chapter and revisiting the research questions stated above.

Table 1.1: Overview of the studies in this dissertation

	Chapter 2	Chapter 3	Chapter 4
Research focus	<ul style="list-style-type: none"> - Effects of physical stores on product purchases and returns in the online channel - Differentiation between purchases/returns of higher- and lower-risk products 	<ul style="list-style-type: none"> - Influence of shipping fee policies on orders (sales, order value, order count) and returns - Comparison of threshold-based free shipping (i.e., shipping fee only for order below a certain value) and fixed-fee shipping 	<ul style="list-style-type: none"> - Effect of price reductions on product returns - Differentiation between price reductions in effect at the time of purchase or post-purchase during the return period - Comparison of product categories
Data	<ul style="list-style-type: none"> - Purchase and return data of 10 000 customers during 6 years - Physical store location data - Large fashion retailer 	<ul style="list-style-type: none"> - Purchase and return data of 3.81 mio. customers during 3 years - Large generalist online retailer 	<ul style="list-style-type: none"> - Purchase and return data of 3.81 mio. customers during 3 years - Daily product pricing data - Large generalist online retailer
Analysis methods	<ul style="list-style-type: none"> - Empirical - Regression using hierarchical Spatial Durbin Error Poisson Model 	<ul style="list-style-type: none"> - Empirical - Cross-sectional time-series regression - Logistical regression 	<ul style="list-style-type: none"> - Empirical - Royston-Parmar spline-based survival regression model - Weighted meta-regression
Main findings	<ul style="list-style-type: none"> - Offline stores reduce returns online - Effect on returns is driven by effect on higher-risk products - Offline stores do not influence online purchases 	<ul style="list-style-type: none"> - Threshold-based free shipping increases order count, sales, and slightly increases returns - Profitability simulation shows positive effect on orders outweigh negative effect on returns 	<ul style="list-style-type: none"> - Price reductions lead to more (less) returns for customers that have (not) returned due to a price reduction previously - Effects independent of when price reduction is in effect

2

When Offline Stores Reduce Online Returns

Contemporary omni-channel retailing combines online and offline stores. A central question then is whether and how offline stores influence online shopping behavior of customers. In an empirical study, the authors address this issue using data from a large Dutch shoe retailer. They develop a novel spatial model to estimate the influence of proximate retail stores on customers' online shopping behavior, while controlling for spatial and customer heterogeneity. Results show that the retailer's offline stores do not significantly affect online product purchases. However, they can decrease the number of returned products per shopping basket, depending on product characteristics.

2.1 Introduction

In recent years, the retail industry has undergone a profound transformation. Driven by customers, who increasingly shop online, retailers have been expanding to the Internet. For the traditional offline retail giant Wal-Mart, e-commerce has become a strategic pillar and the websites of once traditional offline retailers H&M, Asos, and Zara are now among the most-visited e-commerce sites (Deloitte, 2018; Zaczekiewicz, 2018). At the same time, former online-only retailers have embraced an omni-channel strategy and have begun to open or cooperate with offline stores. Examples are Warby Parker, Bonobos (Satell, 2017; Soper, 2018) and, most notably, Amazon, with a growing array of own physical stores in different product categories (e.g. “Amazon Books” bookstores, “Amazon Go” convenience stores, “Whole Foods” stores) and its cooperation with Kohl’s to allow for in-store returns at Kohl’s department stores (Chen, 2019). Ultimately, retailers and “e-tailers” might converge into a common, omni-channel type of business model (CB Insights, 2018; Thompson, 2017).

One crucial aspect in this transition, to both retailers and e-tailers, is the position of physical, offline, stores in their omni-channel portfolio. On the one hand, traditional offline retailers are under rising cost pressure and many physical retail stores have been closed in the past, a development for which the term “retail apocalypse” has been coined (Taylor, 2019). On the other hand, the opening of and cooperation with physical stores by former online-only retailers poses the question, which benefit lies in physical retail stores. Benefits might not only lie in the actual revenue incurred by the offline stores, but also in changing customer behavior with regards to the online channel.

One of the aspects in which traditional retailers who have expanded to the internet in the past differ from e-tailers, is the fact that they already have a strong physical offline presence. Question then becomes whether this offline presence constitutes a competitive advantage relative to the e-tailers with regard to online sales, or whether it is merely a cost that should be reduced: would opening or closing stores harm or help the online business of these traditional retailers?

In this paper, we investigate what effects physical stores of traditional offline retailers have on the customer behavior in their online channel. Online customer behavior pertains to two critical determinants of profitability: (1) the number of product purchases, and (2) the number of product returns (Minnema et al., 2018). In other words, what would happen to purchases and returns if store presence would be increased or decreased? Regarding the former, there might be negative effects between the online and offline channel but also positive signaling effects. Regarding the latter, stores might increase returns by making returns easier and cheaper, but they might also decrease returns by allowing customers to ascertain a satisfactory product fit before ordering. Both might be differently affected by offline stores, depending on the

performance risk associated with the product. Nearby offline stores might change customer purchase or return behavior only for products which need personal fitting and not products which do not, or only for cheaper products and not for more expensive products.

Prior research has generally focused on channel additions, i.e., adding an online channel to an existing offline channel (e.g., Li, 2021; van Nierop et al., 2011; Weltevreden, 2007) or adding an offline channel to an existing online channel (Avery et al., 2012; Pauwels & Neslin, 2015; Wang & Goldfarb, 2017). Findings on the latter type of channel additions are mixed. While Avery et al. (2012) report positive effects of the opening of offline stores on online sales in the long run, Wang and Goldfarb (2017) show both positive and negative effects on online sales, depending on the extent to which customers already purchased in the online channel prior to the opening of the offline store. Pauwels and Neslin (2015), in turn, find no evidence for a difference in online sales due to an increased offline store presence. However, they find that adding offline stores increases the total return frequency across all types of products and all channels, without having distinguished between purchases made in the different channels nor between different types of products. These three studies focused on the establishment of a completely new offline channel in addition to the online channel, the situation of a pure e-tailer becoming a multichannel retailer. For a traditional offline retailer that has become a multichannel retailer, the impact of its offline stores on its online activities has not been examined.

This study builds on the findings of the previous work cited above, and addresses some of the gaps that remain. First, we adopt a holistic view of the impact of offline store presence on the retailer's online channel performance by analyzing the impact on online purchase frequency, online purchase volume, and online product returns. Thereby, we go beyond prior work by Pauwels and Neslin (2015) in providing insights on the impact of the offline channel on purchases *and* returns in the online channel. Second, we investigate how products' risk profiles affect the impact of changes in offline presence on the retailer's online channel performance. The analyses provide an understanding of where and when cross-channel effects are positive or negative, and can shed light on the diverging findings from previous research that only looked at aggregate sales (and returns) across all types of products sold by the respective retailers. Third, we investigate the effects of store *presence* in all national regions instead of store *openings* in retailer-selected regions. In addition, we propose and use a novel model specification, a hierarchical Spatial Durbin Error Poisson model. We thus incorporate the impact of the historical offline presence of the retailer. In sum, we contribute to prior literature by:

- investigating the influence of offline store presence on online purchases – in terms of how often and how much at a time customers order – as well as returns,

- integrating how risk-related product characteristics moderate the influence of offline stores presence, and
- proposing a novel spatial model specification to analyze the effect, avoiding regional selection bias and taking account of the spatial structure of the data.

In our analysis, we use data of 10 000 online customers of a large retailer in the fashion industry, offering a range of products with different characteristics with regard to price and personal fit, over a period of 6 years. Data from this industry are particularly suited, as it is the consumer industry in which e-commerce is most prevalent, with, for example, two thirds of customers in the European Union shopping online for such products (Eurostat, 2021a). As the percentage of e-commerce steadily grows in other product categories, issues that play a role in the fashion sector today might extend to other categories in the future. In our model section, we develop an extended version of the Spatial Durbin Error Model. This allows us to model the effect of stores on customer behavior while taking into account of customer heterogeneity, regional heterogeneity and the (extra-)regional influence of stores, i.e., store influence as a function of distance to the customer.

Results of our analyses show that an increased offline channel presence does not lower the sales in the online channel. Moreover, depending on the products' risk profiles, it helps the retailer by reducing product returns. A simulation study shows that reductions in product returns due to increased offline store availability can amount to 4.83% - 5.65%, depending on the type of product, and this for moderate increases in the number of offline stores. Completely abandoning the offline channel, on the other hand, could increase the number of returns with 15.65%, thereby reducing individual-customer profitability with 5.15%. In consequence, this study shows how omni-channel retailers stand to benefit from the offline channel: by decreasing online channel returns and increasing customer profitability, whereby retailers offering higher-risk products are expected to profit most.

2.2 Theoretical Background

Online and offline channels compete with each other along the whole customer journey, i.e. during pre-purchase, purchase, and post-purchase (Verhoef et al., 2015). During the customer journey, customers can interact with multiple channels (Bijmolt et al., 2019). For example, many customers visit stores – pre-purchase – and subsequently purchase online (so-called show-rooming), or visit a website – pre-purchase – and subsequently purchase the product in a store (so-called web-rooming). However, channel choices are dependent of each other as channels “affect one another because of lock-in effects, channel inertia, and cross-channel synergies” (Lemon & Verhoef,

2016). Therefore, the availability of one channel influences customer behavior across the whole customer journey and across channels. Concerning the consequences of offline channel availability on purchases and returns in the online channel, there might be multiple, competing processes, which we will describe in this section.

2.2.1 Purchases

There are two mechanisms of how the availability of one channel can influence purchases in another channel, and this both in terms of the number of ordered baskets as in terms of number of products per basket. The first mechanism consists of channel presence leading to channel substitution. The second mechanism, in turn, consists of channel presence having a global promotional effect. Both point to a different effect direction, resulting in two opposing hypotheses.

Customers choose channels based on characteristics of the channels, and the ability to fulfil customer preferences. Rohm and Swaminathan (2004) identified six motives for shopping: shopping convenience, information seeking, immediate possession, social interaction, the retail shopping experience and variety seeking. Different shopping channels are suited to a different extent to comply with these motives: Online shopping may score higher on convenience and variety seeking while offline shopping wins on immediate possession and the retail shopping experience (King, 2018; Rekuc, 2018). The ranking of the motives and thereby the ranking of the channels depends on personal preference. For example, variety-seeking customers might have a stronger preference for shopping online while social interaction-favoring customers might have a stronger preference for going to a retail store (Neslin & Shankar, 2009). The relative weights of the different motives and the resulting preferences will vary between consumers. When channel preference is strong relative to retailer preference, the absence of the preferred channel (e.g., offline) will make consumers shop at competing retailers that do offer a nearby offline option. However, when channel preference is relatively weaker vis-à-vis retailer preference, things can look different: When an offline retailer opens an online channel, this may move some of its customers to the online channel (e.g., Li, 2021). The burden of having to travel to a (distant) store is now taken away by the new online channel. However, when that retailer opens a physical store nearby, the relative burden of traveling to a (nearby) store becomes much smaller, possibly tilting the balance in favor of the close offline store instead of the online option. Previous research by Wang and Goldfarb (2017), showing negative effects of the addition of an offline store on online sales in regions where online sales were relatively high, provides evidence for such mechanisms. At an overall level, across customers, online channel purchases are therefore expected to be lower in presence of the offline channel, albeit that effects are likely small. Since this could translate to both less frequent orders, i.e., less ordered shopping baskets,

and/or smaller orders, i.e., less purchased products per shopping basket, we hypothesize the following:

H1a Offline channel presence decreases the number of ordered shopping baskets.

H2a Offline channel presence decreases the number of purchased products per shopping basket.

On the other hand, stores can also have a promoting function (Mitra & Fay, 2010) due to their mere presence, and can thus convert non-shoppers in the online channel to shoppers in that channel. Such non-shoppers can be existing customer from the offline channel as well as new customers who used to shop at competitors in the offline channel. Customers can be primed in the need recognition phase by seeing stores of a brand to visit the web shop of this brand. Moreover, customers can also change channels in a later stage, as is exemplified by the phenomenon of show-rooming. Here, customers deliberately visit a store to choose a product without purchasing it. Instead, they change channels for the actual purchase. Both phenomena could explain why especially in areas where online sales are relatively low, adding offline stores may thus boost online sales (Wang & Goldfarb, 2017). In general, the existence of the offline channel can thus draw customers to make purchases in the online channel. Again, this might result in both more frequent orders, i.e., more ordered shopping baskets, and/or larger orders, i.e., more purchased products per shopping basket. Therefore, we hypothesize the following:

H1b Offline channel presence increases the number of ordered shopping baskets.

H2b Offline channel presence increases the number of purchased products per shopping basket.

2.2.2 Returns

The presence of an offline channel can also influence the number of product returns. As before, we focus on the effect on the online channel, i.e., products returned that were purchased in the online channel. Again, two mechanisms with opposite directionality are at play, resulting in two opposing hypotheses.

On one side, the offline channel might decrease returns due to customers' reaction to perceived risk (Kushwaha & Shankar, 2013). According to V. W. Mitchell (1992), social risk, financial risk, physical risk, performance risk, time risk and psychological risk can influence consumer behavior. For fashion products – the type of products that we focus on – performance risk is pronounced (Gu & Tayi, 2015). For such products, performance is to a great extent determined by product fit, i.e., the match

between customer preferences and product properties (Anderson et al., 2009). The amount of uncertainty concerning product fit depends on channel choice, as offline stores allow for much better inspection of physical products than an online website. Customers can anticipate this increased uncertainty and the resulting increased likelihood of returning and adapt their purchase behavior accordingly (Janakiraman & Ordóñez, 2012). In particular, when offline stores are available, customers can shift the first stages of their decision-making process to offline stores. That is, they would engage in show-rooming to reduce fit uncertainty. For the final purchase, however, consumers may move to the online stores, as they may want to take some time to evaluate the different options before the actual purchase or want to benefit from the convenience of purchases delivered at home. As a result, subsequent returns of such purchases made in the online channel are likely lower. In addition, customers can shift the whole customer journey to the stores, becoming “one-stop shoppers” in the offline channel (Neslin & Shankar, 2009). Regarding the return rate, results would be the same: customers would return less in the online channel. Therefore, we hypothesize the following:

H3a Offline channel presence decreases the number of returned products per shopping basket.

On the other side, returns might increase due to decreased “cost” of returning. It has been shown that the effort it takes to return a product influences the likelihood that customers actually return a product (Kim & Wansink, 2012). The decision to return a product is a result of a cost/benefit calculation. Even though a product might not ideally fit the customer’s preferences, returning the product is associated with a cost. The cost of returning the product must be lower than the shortcoming in utility of the product in order for a return to be worthwhile (Anderson et al., 2009; Petersen & Kumar, 2015). When there is no offline channel available, customers must re-package the product in a parcel, label it, drive to a post office and, sometimes, pay shipping fees. In addition, a refund will usually be offered only after the firm received the product back and checked its condition. On the other hand, when stores are available, customers can simply return the product there, thereby avoiding shipping fees, investment in time and effort, and packaging. In consequence, returning costs for the customer are lower when the offline channel is available. Therefore, the cost/benefit calculation is likely more often in favor of returning and, thus, customers might also return more, leading to the following hypothesis:

H3b Offline channel presence increases the number of returned products per shopping basket.

The Role of Risk

Purchasing a product is generally associated with risk. As argued above, fashion products suffer from performance risk due to uncertainty regarding the fit between product properties and customer preferences (Anderson et al., 2009; Gu & Tayi, 2015). While all products have some risk, the relative amount of risk differs, however.

In particular, whether or not a product fits, i.e., its fit uncertainty, depends on the type of product: A first type of fashion products is highly dependent on the customer's physiology. Such products are generally offered in multiple sizes (e.g., XS, M, XXL) and, by consequence, pre-purchase fit uncertainty is higher. Conversely, a second type of fashion products is mostly independent of the customer's physiology. Such products are therefore offered only in one size (e.g., bags and watches) and, by consequence, pre-purchase fit uncertainty is lower. Despite technological advances in the online channel (e.g., zoomable product images, Minnema et al., 2016), customers still need to visit a store and check their personal physiology in combination with the product to eliminate fit uncertainty. When more offline stores are available to customers with a stronger retailer preference compared to the channel preference, customers can more easily reduce fit uncertainty by visiting a store either before ordering online or even instead of ordering online. This will especially be relevant for products with higher levels of fit uncertainty where customers will more actively look for options to reduce this uncertainty. When customers visit a store before ordering online, fit uncertainty and thereby returns are likely reduced and when customers visit a store instead of ordering online, both purchases and returns are likely reduced. In sum, we expect offline store availability to have a negative effect on purchases and returns for the online channel for high fit-uncertainty multi-size products. For purchases and returns of low fit-uncertainty uni-size products, we expect effects to be limited or even absent.

In addition, performance risk of a product also depends on customers' expectations. Customers have higher quality expectations for products that are relatively more expensive (Grewal, 1995). For products that are perceived as less expensive (i.e., due to a low price relative to competitors or having a price discount), customers might be more willing to accept slight deficits in the product. Consequently, perceived performance risk is lower for such products. Therefore, customers will feel less the need to reduce the risk by interacting with the offline channel instead of or before interacting with online channel. However, when perceived performance risk becomes higher, the need to mitigate this risk also becomes stronger, and the availability of ways to do so becomes more salient. While an increase in the number of offline stores may be less relevant for products with a low perceived performance risk, it will be more relevant in case of products with a high perceived performance risk. In consequence, we expect availability of offline stores to have a negative effect on both purchases

and returns in the online channel for (high-risk) undiscounted and relatively higher-priced products. For purchases and returns of (low-risk) discounted and relatively lower-priced products, we expect effects to be limited or even absent. In sum, we expect risk level with regards to fit uncertainty, price level and discount to moderate the effect of offline channel presence on both purchases and returns (Figure 2.1). Therefore, we hypothesize that:

H4a-b-c The impact of offline channel presence on the number of purchased products per shopping basket is more negative/less positive for (a) products with higher fit uncertainty (i.e., multi-size products), (b) higher-priced products, and (c) undiscounted products compared to products with lower fit uncertainty, lower-priced products, and discounted products, respectively.

H5a-b-c The impact of offline channel presence on the number of returned products per shopping basket is more negative/less positive for (a) products with higher fit uncertainty (i.e., multi-size products), (b) higher-priced products, and (c) undiscounted products compared to products with lower fit uncertainty, lower-priced products, and discounted products, respectively.

Figure 2.1: Research framework

2.3 Data

2.3.1 Sample

To assess the impact of offline channel availability on the customer purchase and return behavior in the online channel, we conduct an empirical analysis with data from a large Dutch retailer in the fashion segment that sells shoes, bags, belts, socks, wallets and similar products. We have a sample of 10 000 online customers who ordered at least one product during a period from September, 8th, 2008 to October, 5th, 2014. In total, customers ordered more than 20 000 products (in about 15 000 shopping trips or baskets) and returned more than 3500 products in this period. Orders could be delivered at home or picked up in one of the stores. Generally, for each product order, we have detailed information on the product that was ordered and the customer who ordered it. In a small number of cases, product or customer information is missing and we had to remove the associated orders from the dataset (see section Invalid Cases and Missing Variables).

The address of the customer serves to assign each customer to one region. The regions are defined using zip-codes – i.e., each region comprises the area which is covered by the same 4-digit zip-code – which leads to relatively small and contiguous regions. This allows us to examine the influence of the retailer’s offline stores on customers’ online shopping behavior while taking proximity into account. The number of stores is rather stable over time, ranging from 405 in 2005 to 430 in 2017, with a peak of 460 in 2012. We gather the location of the retailer’s stores – and the associated zip-code region – from a database of store locations (schoenenwinkelsoverzicht.nl, assessed in June, 2017). The average size of a region is 10.900km^2 ($\text{sd} = 20.276\text{km}^2$).

Using the store location data, we calculate our explanatory variable store availability. In particular, we use the count of stores within each zip-code region plus the count of stores beyond that region and apply spatial decay for the latter (we provide more information on the so-called spatial decay in the Model section).

2.3.2 Variables

For our analysis, we use the following dependent variables: the number of ordered shopping baskets per customer, the number of purchased products per shopping basket, and the number of returned products per shopping basket. Decomposing the total number of purchases and returns into ordered shopping baskets and purchases/returns per shopping baskets has two benefits: First, it allows to separately assess (1) how many times customers order, and (2) how much they purchase and return per order. Second, it allows to add order-level control variables to the analysis of (2).

We expect store availability to have a different influence for products of different price levels, discounts and sizes. Thus, we separately analyze purchases and returns of three pairs of complementing subsets of products, namely the subsets of products with either (1) higher or lower fit uncertainty, (2) with higher or lower price, and (3) without or with a discount. For distinguishing higher- from lower-priced products, we use a within-category median split of undiscounted product prices. Using a within-category split instead of an across-category split is based on the notion that cheap categories can still contain relatively expensive – and thus risky – products and vice versa. In total, we thus have seven sets of products: one set with all products, and three times two complementary sets. For each set, we analyze purchases and returns, resulting in 14 outcome variables (Table 2.1).

Table 2.1: Product purchase and return variables

K	Variables	Description
$k = 0$	$\text{purchases}_{i,c,r,0}$ $\text{returns}_{i,c,r,0}$	Number of overall purchased/returned products ¹
$k = 1$	$\text{purchases}_{i,c,r,1}$ $\text{returns}_{i,c,r,1}$	Number of purchased/returned multi-size products ¹
$k = 2$	$\text{purchases}_{i,c,r,2}$ $\text{returns}_{i,c,r,2}$	Number of purchased/returned uni-size products ¹
$k = 3$	$\text{purchases}_{i,c,r,3}$ $\text{returns}_{i,c,r,3}$	Number of purchased/returned products priced above the median price in their category ¹
$k = 4$	$\text{purchases}_{i,c,r,4}$ $\text{returns}_{i,c,r,4}$	Number of purchased/returned products priced below the median price in their category ¹
$k = 5$	$\text{purchases}_{i,c,r,5}$ $\text{returns}_{i,c,r,5}$	Number of purchased/returned products without discount ¹
$k = 6$	$\text{purchases}_{i,c,r,6}$ $\text{returns}_{i,c,r,6}$	Number of purchased/returned products with discount ¹

¹ in shopping basket i of customer c in region r

As control variables, we use demographic information, month and year of the order and additional regional information like welfare, urbanization, car ownership, and post office locations. The latter originate from Statistics Netherlands (CBS), the Netherlands Institute for Social Research (SCP) and the Dutch post (PostNL), respectively. For post offices, we reverse geo-coded their geographical coordinates to zip-code regions using the ArcGIS services API (ESRI, 2016) and included a count with spatial decay as a control variable, similar to our approach of including retail store locations which is also based on zip-code regions.

2.3.3 Invalid Cases and Missing Variables

In some cases, the data contained incomplete or unusable information on ordered products or customers. First, we removed the product orders for which product characteristics were missing as we cannot estimate the influence of product characteristic-based moderators. Second, we removed product orders, where customers could not be assigned to a region or regional statistical information was not available. In total, we removed 57 full customers (from 10 000 to 9943, i.e., .57%), 705 entire shopping baskets (from 15 122 to 14 426, i.e., 4.60%), and 1171 specific product purchases (from 21 360 to 20 189, i.e., 5.48%).

Data on gender and age is only available for a portion of the data (percentage observed: 49.3% for gender, 46.3% for age). Deleting all cases with missing data would dramatically shrink the sample size and hence statistical power (Graham, 2009). Therefore, for age, we add an additional dummy variable to indicate missingness and set the missing data value itself to the mean of non-missing data. For gender, we only add an additional dummy variable to indicate missingness.

2.3.4 Descriptive Overview

In Table 2.2, we present a description of all variables, that we include in our analysis. In total, we observe 14 426 ordered shopping baskets by 9943 customers. A customer orders on average 1.451 shopping baskets ($sd = 1.044$, range 1 – 18). A shopping basket contains on average 1.399 purchased products ($sd = .826$, range 1 – 17) and .251 returned products ($sd = .649$, range 0 – 10). Customer identified predominantly as female (86.63% of the observed gender) and were 40.524 years on average ($sd = 11.314$). The average number of stores of our retailer per region is .121 ($sd = .594$, range 0 – 12).

2.4 Methodology

We employ three hierarchical spatial regression models to estimate the effects of store availability. First, we estimate a model for the number of shopping baskets ordered by a customer over the period of observation, dependent on the number of stores in proximity – in addition to several other control variables including the customers' age and gender to account for customer heterogeneity. We account for distance by pre-multiplying a weighting matrix W to the vectors stores and posts. This operation adds to the two variables the spatially decayed (i.e., diminished) values of neighboring regions. By that, a higher number of stores in one region increases also the number of stores in proximate regions, but to a lesser extent the higher the distance between both regions. The further two regions A and B are apart, the less the stores of region

Table 2.2: Variables used in the purchase and returns models

Variable	Description
Customer behavior	
$\text{baskets}_{c,r}$	Number of ordered shopping baskets by customer c in region r
$\text{purchases}_{i,c,r,k}$	Number of purchased products in shopping basket i of customer c in region r with product characteristic k
$\text{returns}_{i,c,r,k}$	Number of returned products in shopping basket i of customer c in region r with product characteristic k
Regional characteristics	
$(W \times \text{stores})_r$	Number of stores in region r and its surrounding regions with spatial decay
$(W \times \text{posts})_r$	Number of post offices in region r and its surrounding regions with spatial decay
welfare_r	welfare indicator ¹ for region r
urbanization_r	urbanization indicator ¹ for region r
cars_r	cars per capita ¹ in region r
Order characteristics	
year_i	Year in which the order i was made (0 = 2008, ..., 6 = 2014)
$\text{month}_{2,i}, \dots, \text{month}_{12,i}$	11 indicators for the month in which order i was made (baseline: January)
Customer characteristics	
age_c	Age of customer c in years ¹
gender_c	Customer c is female (1) or male (0)

¹ mean-centred

A will count in the total store value of region B (and vice versa). Furthermore, we add a regional error term for unobserved regional heterogeneity. Since proximate regions are more similar to each other than distant regions, we permit spatial auto-correlation in the regional error term: the closer the regions are, the stronger they will resemble each other, and the more they will be correlated. In the subsection “Spatial Durbin Error Model”, we describe the spatial aspect of our model in more detail. We assume a zero-truncated Poisson distribution for the dependent variable, because all customers in the sample order at least once. The resulting, first model is shown in (2.1):

$$\begin{aligned}
\text{baskets}_{c,r} &\sim \text{ztPoisson}(\exp(\mu_{\text{baskets}_{c,r}})), \\
\mu_{\text{baskets}_{c,r}} &= \alpha_1 + \beta_1 \text{age}_c + \beta_2 \text{gender}_c \\
&\quad + \theta_1 \text{welfare}_r + \theta_2 \text{urbanisation}_r + \theta_3 \text{cars}_r \\
&\quad + \gamma_1 (W \times \text{stores})_r + \gamma_2 (W \times \text{posts})_r \\
&\quad + u_r, \\
u_r &= (I_J - \lambda_k W_u)^{-1} \varepsilon_r, \quad \varepsilon_r \sim N(0, \tau_k).
\end{aligned} \tag{2.1}$$

Second, we estimate a model for the number of purchased products per shopping basket, as shown in (2.2). We estimate the same model for all purchases $_{i,c,r,k}$ variables shown in Table 2.1. For purchases $_{i,c,r,0}$ we assume a zero-truncated Poisson distribution since all baskets contain at least one product of any sort and for the remaining orders variables we assume a regular Poisson distribution. We account for observed customer heterogeneity by including age and gender in the model, and add a customer-level random effect to account for further unobserved heterogeneity.

$$\begin{aligned}
\text{purchases}_{i,c,r,0} &\sim \text{ztPoisson}(\exp(\mu_{\text{purchases}_{i,c,r,0}})), \\
\text{purchases}_{i,c,r,k} &\sim \text{Poisson}(\exp(\mu_{\text{purchases}_{i,c,r,k}})) \quad \forall k \in \{2..7\}, \\
\mu_{\text{purchases}_{i,c,r,k}} &= \alpha_{1,k} + \beta_{1,k} \text{year}_i + \sum_{m=2}^{12} \beta_{2,m,k} \text{month}_{m,i} \\
&\quad + \beta_{3,k} \text{age}_c + \beta_{4,k} \text{gender}_c \\
&\quad + \theta_{1,k} \text{welfare}_r + \theta_{2,k} \text{urbanisation}_r + \theta_{3,k} \text{cars}_r \\
&\quad + \gamma_{1,k} (W \times \text{stores})_r + \gamma_{2,k} (W \times \text{posts})_r \\
&\quad + \varepsilon_{c,k} + u_{r,k}, \\
\varepsilon_{c,k} &\sim N(0, \sigma_k), \quad u_{r,k} = (I_J - \lambda_k W_u)^{-1} \varepsilon_{r,k}, \quad \varepsilon_{r,k} \sim N(0, \tau_k).
\end{aligned} \tag{2.2}$$

Third, we estimate a model for the number of returned products per shopping basket, as shown in (2.3). We estimate the same model separately for all returns $_{i,c,r,k}$ variables shown in Table 2.1 and we always assume a regular Poisson distribution

for the dependent variable. Similar to before, we control for regional and customer heterogeneity as well as year and month:

$$\begin{aligned}
 \text{returns}_{i,c,r,k} &\sim \text{Poisson}(\exp(\mu_{\text{returns}_{i,c,r,k}})), \\
 \mu_{\text{returns}_{i,c,r,k}} &= \alpha_{1,k} + \beta_{1,k}\text{purchases}_i + \beta_{2,k}\text{year}_i + \sum_{m=2}^{12} \beta_{3,m,k}\text{month}_{m,i} \\
 &\quad + \beta_{4,k}\text{age}_c + \beta_{5,k}\text{gender}_c \\
 &\quad + \theta_{1,k}\text{welfare}_r + \theta_{2,k}\text{urbanisation}_r + \theta_{3,k}\text{cars}_r \\
 &\quad + \gamma_{1,k}(W \times \text{stores})_r + \gamma_{2,k}(W \times \text{posts})_r \\
 &\quad + \varepsilon_{c,k} + u_{r,k}, \\
 \varepsilon_{c,k} &\sim N(0, \sigma_k), \quad u_{r,k} = (I_J - \lambda_k W_u)^{-1} \varepsilon_{r,k}, \quad \varepsilon_{r,k} \sim N(0, \tau_k).
 \end{aligned} \tag{2.3}$$

In sum, we use separate models to identify whether a customer (a) orders more often (i.e., more shopping baskets), (b) purchases more products at a time (i.e., more products per shopping basket), and/or (c) returns more products per shopping basket. This allows us to assess consumer behavior in more detail than only estimating a model of total product purchases/returns and conflating order frequency and quantity.

2.4.1 Spatial Durbin Error Model

In our models, we use both spatial predictors and a spatial error term. The use of spatial predictors follows the idea that “responses by individuals are [...] correlated in such a manner that individuals near one another in the space generate similar outcomes” (Bradlow et al., 2005, p. 268). More formally, an observed outcome of unit A does not only depend on characteristics of entity A, but also on characteristics of neighboring entity B, C and so on. This is called spatial dependence. Spatial models reflect that process by incorporating the influence of neighboring entities into the regression equation, weighted by a metric of their distances. The use of a spatial error term follows the idea that spatially situated observations are influenced more or less by the same unobservable factors (e.g., infrastructure, culture), depending on their distance to each other. This would normally lead to heteroskedasticity in the error term, but can be dealt with by a spatial model by explicitly modelling autocorrelated errors. Using both spatial predictors and a spatial error term is termed the spatial Durbin error model (Halleck Vega & Elhorst, 2015). In its most basic form, it looks as follows:

$$Y = X_A \beta + W X_B \theta + u \tag{2.4}$$

$$\begin{aligned} \text{with: } u &= \lambda W u + \varepsilon, \\ \varepsilon &\sim N(0, \sigma^2 I_n). \end{aligned}$$

The dependent variable Y_i of observation i is influenced by the independent variables in X_A belonging to the same observation i and a linear combination of independent variables in X_B of possibly all other observations, through pre-multiplying the data vector or matrix with the square weighting matrix W . Thus, how neighbors influence each other is defined by the matrix W . The weighting matrix W is also used to model the autocorrelation between error terms ($u = \lambda W u$).

We modify this model to estimate both own-region and cross-region effects with θ by including the diagonal in W . Furthermore, we restrict the parameter range of λ to a maximum of one by scaling the matrix W used in the formula to calculate u (LeSage & Pace, 2009). The resulting matrices are

$$W \text{ with } W_{i,j} = \begin{cases} \exp(-\frac{2}{10}D_{i,j}), & \text{if } \exp(-\frac{2}{10}D_{i,j}) > 10\%, \\ 0, & \text{otherwise} \end{cases}, \quad (2.5)$$

$$W_u = \frac{1}{v-1}(W - I), \quad (2.6)$$

with $D_{i,j}$ being the distance between i and j , and v the largest eigenvalue of W . We assume an exponential decay with a cut-off at an influence of less than 10%, which corresponds to $D_{i,j} > 11.5\text{km}$. A cut-off value is necessary to generate a sparser matrix and make computation more efficient. For $D_{i,j}$, we use the linear distance between the centroids of each zip-code region.

The spatial Durbin error model is the preferred spatial model when modelling local spillover effects (Elhorst, 2014; LeSage, 2014). However, the model shown above has some limitations we need to address. First, the model is non-hierarchical which makes it unsuitable for most marketing applications. We therefore add a second level to the model, thereby building on the work by Lacombe and McIntyre (2016). Such second hierarchy level allows to express the nesting of multiple customers within one spatial region. As shown above, we coalesce regional effect within- and beyond-region effects so that we have one parameter estimate per regional influential factor. Second, to be able to estimate effects on discrete (instead of continuous) outcomes, we use a Poisson (or zero-truncated Poisson) distribution instead of a Normal distribution. Since multivariate count distributions have a range of issues with regards to theoretical feasibility, computability and interpretability – with no generally agreed-upon solution (see e.g., Inouye et al., 2017), we model the influences on each dependent variable separately using a (zero-truncated) univariate Poisson distribution for each of the resulting hierarchical Spatial Durbin Error Poisson models.

2.4.2 Estimation

We use a Bayesian approach to obtain the estimates for the models. Such approach offers flexibility in tailoring the models to the specific requirements of the topic at hand (e.g., LeSage & Pace, 2009, p.124), and at the same time accommodates the hierarchical structure of the error terms in our models (Lacombe & McIntyre, 2016, e.g.,). In particular, we use the No-U-Turn Markov Chain Monte Carlo sampling (NUTS) provided by the Stan software package (Stan Development Team, 2017). We use uninformative (uniform) priors for all parameters. The error structure of the model requires to compute the inverse of a function of the spatial weighting matrix W at each sampling step. The high number of regions and the resulting high dimensionality of the spatial weight matrix, however, renders this computationally unfeasible. Instead, we approximate the inverse by a Neumann series. When estimating, all relevant parameters of all models converged, with their so-called potential scale reduction factor (PSRF or $\hat{R}$) being smaller than 1.1. We also tested the model by simulating data and comparing the true to the estimated parameters. Here as well, results were satisfying. Finally, we checked for multicollinearity among the included variables. All VIF scores are well below the critical value of 5 (Leeflang et al., 2015) with a highest value of 4.13, confirming that the models do not suffer from multicollinearity. More details on simulation, model estimation and convergence can be found in the Appendix (section 6.1).

2.5 Results

We first share some model-free insights, and then report the model-based results on the influence of offline stores on the number of shopping baskets customers order online. Next, we present the influence of stores on the number of purchased and returned products per shopping basket, when including all products. Finally, we report the influence of stores on purchases and returns per shopping basket for complementing subsets of products, namely based on price level, discounting, or size.

2.5.1 Model-Free Insights

Figure 2.2 shows that the number of ordered baskets is relatively equal for lower numbers of stores in proximity (1.46, 1.43, and 1.45), but then drops for the higher numbers of stores in proximity (1.39 and 1.36). However, overall, there is no evidence of a significant effect, with the correlation between the number of ordered shopping baskets and number of stores in proximity being insignificant (-0.017 , $p > .10$).

The number of purchases per shopping basket also appears to become lower for the higher numbers of stores in proximity (Table 2.3), although this picture is not con-

Figure 2.2: Ordered shopping baskets per customer for different numbers of stores in proximity

stant across product types with different risk levels. Overall, across all product types, there is no evidence of a significant effect, with the correlation between the number of purchases per shopping basket and the number of stores in proximity being insignificant (.015, $p > .10$). The number of returns per shopping basket, on the other hand, shows a stronger negative relation with the number of stores in proximity, and this both overall and for all product types with different risk levels. The strongest correlations can be found for the higher-risk product types: multi-size products ($-.062$, $p < .001$), products priced above the median in their category ($-.063$, $p < .001$), and products without discount ($-.060$, $p < .001$).

2.5.2 Ordered Shopping Baskets

Table 2.4 presents the estimation results for the model explaining the number of ordered shopping baskets per customer. The availability of offline stores of the retailer does not help or harm the online channel, as it does not significantly influence the number of ordered shopping baskets ($-.046$, 95% credibility interval (CI): $-.127$, $.032$). Thus, we find no empirical support for H1a or H1b.

Regarding demographic control variables, customers with a higher age order more (.003, CI: $.000$, $.007$) and customers who do not disclose their age or gender order less ($-.250$, CI: $-.319$, $-.180$; and -1.215 , CI: -1.312 , -1.113 respectively). Regional control variables are generally insignificant at the 5% level with the exception of car ownership (.213, CI: $.019$, $.390$). There is significant heterogeneity at the regional level (.572, CI: $.527$, $.619$) and significant spatial auto-correlation (.335, CI: $.010$, $.857$).

Table 2.3: Number of purchases and returns per basket for different numbers of stores in proximity and the associated correlation

Stores in proximity ($W \times$ stores):	[0,3.33)	[3.33,6.67)	[6.67,10)	[10,13.3)	[13.3,16.9)	Correlation ¹
<i>Purchases:</i>						
Overall	1.39	1.41	1.45	1.41	1.07	.015
Multi-size	1.33	1.36	1.41	1.34	1.07	.022**
Uni-size	.06	.05	.04	.07	.00	-.024**
Price above median	.89	.80	.82	.93	.67	-.047***
Price below median	.51	.61	.63	.48	.40	.060***
Undiscounted	1.00	.99	1.04	1.13	1.00	.015
Discounted	.39	.42	.41	.27	.07	.000
<i>Returns:</i>						
Overall	.28	.21	.19	.16	.00	-.064***
Multi-size	.27	.20	.19	.16	.00	-.062***
Uni-size	.01	.01	.00	.00	.00	-.018*
Price above median	.18	.13	.11	.12	.00	-.063***
Price below median	.10	.07	.08	.04	.00	-.025**
Undiscounted	.20	.14	.13	.15	.00	-.060***
Discounted	.08	.07	.06	.02	.00	-.027**
Observations	9688	3510	1048	165	15	

¹ *** $p < .001$, ** $p < .01$, * $p < .05$

2.5.3 Purchases and Returns per Shopping Basket

Table 2.5 presents the estimation results for the models explaining the number of purchases and returns per shopping basket. Again, we find no evidence that the availability of offline stores helps or harms the online channel in terms of purchased products per shopping basket, as it does not significantly influence the number of purchased products per shopping basket (-.039, CI: -.101, .024). Therefore, we find no support for H2a or H2b. However, the availability of offline stores has a beneficial effect on returns per shopping basket as it significantly decreases the number of returned products per shopping basket (-.127, CI: -.216, -.038), which is empirical evidence for H3a (and against H3b).

Regarding control variables, men return less than women (-.511, CI: -.682, -.346) and customers who do not disclose their gender have both fewer purchases and returns (-.511, CI: -.682, -.346; and -.320, CI: -.434, -.206 respectively). Conversely, customers who do not disclose their age return more (.158, CI: .040, .275). Both purchases and returns increase over time (.197, CI: .165, .230; and .075, CI: .034, .115 respectively). Several regional control variables have a significant effect, as well: post office availability increases purchases (.068, CI: .012, .126), car ownership increases purchases (.222, CI: .065, .375) and decreases returns (-.437, CI: -.749, -.143), and urbanization

Table 2.4: Regional influence on the number of ordered shopping baskets

DV	baskets _c	
Intercept	−.002	(−.061, .056)
$(W \times \text{stores})_r$	−.046	(−.127, .032)
<i>Regional control variables</i>		
$(W \times \text{posts})_r$	.066	(−.013, .146)
welfare _r	−.000	(−.038, .039)
urbanization _r	−.008	(−.048, .033)
cars _r	.223	(.019, .390)*
<i>Customer control variables</i>		
gender_man _c	−.065	(−.160, .027)
gender_missing _c	−1.215	(−1.312, −1.113)***
age _c	.003	(.000, .007)*
age_missing _c	−.250	(−.319, −.180)***
<i>Random effects and spatial autocorrelation</i>		
τ (random effect region)	.572	(.527, .619)***
λ (spatial auto-correlation)	.335	(.010, .857)***

Numbers in brackets indicate the 95% credible interval (CI) and stars indicate whether the 95% (*), 99% (**), 99.9% (***) CI excludes zero.

decreases returns ($-.061$, CI: $-.106, -.016$). For both purchases and returns, there is significant spatial auto-correlation ($.492$, CI: $.030, .973$; and $.585$, CI: $.041, .986$ respectively), and significant heterogeneity on the customer ($.736$, CI: $.698, .776$; and $.785$, CI: $.723, .850$, respectively) and regional level ($.056$, CI: $.003, .144$; and $.196$, CI: $.034, .325$, respectively).

2.5.4 Influence of Risk

Table 2.6 presents the estimation results for the models explaining the number of purchases and returns per shopping basket for the subsets of products with multiple sizes (multi-size) and the with one size (uni-size). The availability of offline stores does not significantly harm purchases in the online channel of products of either subset ($-.015$, CI: $-.041, .012$; and $.126$, CI: $-.034, .281$ respectively). Thus, we find no support for H4a. However, the availability of offline stores does have a beneficial influence on product returns as it reduces the number of returns per shopping basket of multi-size products ($-.123$, CI: $-.212, -.037$). In line with our reasoning, it has no significant influence on returns of uni-size products ($-.365$, CI: $-1.147, .395$). Thus, we find support for H5a.

Table 2.7 shows the estimation results for the models explaining the number of purchases and returns per shopping basket for the subsets of lower- and higher-price products, respectively. As before, the availability of offline stores has no significant harmful effect for either set of products in terms of number of purchases ($-.018$, CI: $-.069, .034$; and $-.006$, CI: $-.041, .031$ respectively). Thus, we find no empirical evidence for H4b. However, the availability of offline stores again has a beneficial effect by decreasing returns per shopping basket in the case of more expensive products ($-.132$, CI: $-.240, -.029$) and, as argued, it has no significant influence on returns of cheaper products ($-.127$, CI: $-.283, .028$). Thus, we find support for H5b.

Table 2.8 presents the estimation results for the models explaining the number of purchases and returns per shopping basket for the subsets of discounted and undiscounted products. The influence of offline store availability on purchases/returns of discounted and undiscounted products is in line with the effect of store availability on purchases/returns of cheaper and more expensive products. That is, the availability of offline stores has no significant influence on purchases of both discounted products and undiscounted products ($.001$, CI: $-.060, .064$; and $-.009$, CI: $-.039, .022$ respectively). Thus, we find no support for H4c. Similar to before, the availability of offline stores decreases returns of undiscounted products ($-.153$, CI: $-.249, -.057$) while not affecting returns of discounted products ($-.068$, CI: $-.237, .096$), however. Thus, we find support for H5c.

Table 2.5: Regional influences on the general number of purchases and returns (per shopping basket) in the online channel

DV	purchases _i		returns _i	
Intercept	-2.000	(-2.193, -1.817)***	-2.879	(-3.111, -2.652)***
($W \times \text{stores}$) _r	-.039	(-.101, .024)	-.127	(-.216, -.038)**
<i>Regional control variables</i>				
($W \times \text{posts}$) _r	.068	(.012, .126)*	-.059	(-.140, .022)
welfare _r	-.027	(-.058, .002)	-.015	(-.056, .025)
urbanization _r	.012	(-.021, .045)	-.061	(-.106, -.016)*
cars _r	.222	(.065, .375)**	-.437	(-.749, -.143)**
<i>Customer control variables</i>				
gender_man _c	-.024	(-.136, .088)	-.511	(-.682, -.346)***
gender_missing _c	-.244	(-.333, -.157)***	-.320	(-.434, -.206)***
age _c	.000	(-.004, .005)	.003	(-.003, .009)
age_missing _c	.033	(-.056, .128)	.158	(.040, .275)**
<i>Order control variables</i>				
purchases _i	n.a.		.572	(.543, .600)***
year _i	.197	(.165, .230)***	.075	(.034, .115)***
month _{i,2}	.037	(-.149, .222)	-.135	(-.345, .073)
month _{i,3}	.383	(.235, .536)***	.058	(-.128, .241)
month _{i,4}	.487	(.339, .633)***	.028	(-.148, .201)
month _{i,5}	.459	(.316, .602)***	-.000	(-.179, .178)
month _{i,6}	.496	(.349, .645)***	.109	(-.073, .287)
month _{i,7}	.687	(.548, .833)***	-.271	(-.453, -.082)**
month _{i,8}	.479	(.332, .628)***	-.233	(-.428, -.041)*
month _{i,9}	.315	(.171, .464)***	-.438	(-.628, -.249)***
month _{i,10}	.427	(.278, .575)***	-.238	(-.429, -.050)**
month _{i,11}	.130	(-.047, .298)	-.073	(-.280, .122)
month _{i,12}	.406	(.241, .562)***	-.151	(-.356, .044)
<i>Random effects and spatial autocorrelation</i>				
σ (random effect customer)	.736	(.698, .776)***	.785	(.723, .850)***
τ (random effect region)	.056	(.003, .144)***	.196	(.034, .325)***
λ (spatial auto-correlation)	.492	(.030, .973)***	.585	(.041, .986)***

Numbers in brackets indicate the 95% credible interval (CI) and stars indicate whether the 95% (*), 99% (**), 99.9% (***) CI excludes zero.

Table 2.6: Regional influences on online purchasing and returning (per shopping basket) for uni-size products vs. multi-size products

DV	uni-size products		multi-size products	
	purchases _i	returns _i	purchases _i	returns _i
Intercept	-3.572***	-8.908***	-.074	-2.902***
$(W \times \text{stores})_r$	.126	-.365	-.015	-.123**
<i>Regional control variables</i>				
$(W \times \text{posts})_r$	-.150*	-.234	.028*	-.060
welfare _r	.062	-.119	-.011	-.013
urbanization _r	-.150***	.141	.010	-.068**
cars _r	-.010	-.716	.087*	-.475***
<i>Customer control variables</i>				
gender_man _c	-.956***	-.893*	.016	-.513***
gender_missing _c	-.010	n.a.	-.082***	-.319***
age _c	-.003	-.053*	.000	.004
age_missing _c	-.067	.571	.014	.151*
<i>Order control variables</i>				
purchases _i	n.a.	3.045***	n.a.	.596***
year _i	.013	-.133	.057***	.077***
month _{i,2}	.243	-1.701	-.022	-.124
month _{i,3}	-.105	.577	.111**	.048
month _{i,4}	-.611**	.505	.152***	.007
month _{i,5}	.087	.502	.127***	-.016
month _{i,6}	-.116	.750	.147***	.088
month _{i,7}	-.285	-.439	.249***	-.285**
month _{i,8}	.052	.621	.148***	-.252*
month _{i,9}	-.081	.260	.090*	-.460***
month _{i,10}	-.418*	-.005	.124***	-.243*
month _{i,11}	.321	.070	.019	-.077
month _{i,12}	.711***	-.246	.056	-.133
<i>Random effects and spatial autocorrelation</i>				
σ (random effect customer)	1.254***	2.149***	.010***	.780***
τ (random effect region)	.117***	.627***	.010***	.203***
λ (spatial auto-correlation)	.506***	.499***	.500***	.601***

Stars indicate whether the 95% (*), 99% (**), 99.9% (***) CI excludes zero. Missing and male gender dummies have been collapsed due to low case count for returns of uni-size products.

Table 2.7: Regional influences on online purchasing and returning products (per shopping basket) priced below or above the median price

DV	products priced below median		products priced above median	
	purchases _i	returns _i	purchases _i	returns _i
Intercept	−1.034***	−4.035***	−.547***	−3.414***
($W \times \text{stores}$) _r	−.018	−.127	−.006	−.132*
<i>Regional control variables</i>				
($W \times \text{posts}$) _r	.044	−.060	.002	−.063
welfare _r	.019	−.029	−.029***	.011
urbanization _r	.052***	−.052	−.023**	−.055*
cars _r	.106	−.375	.113**	−.557***
<i>Customer control variables</i>				
gender_man _c	.157***	−.476***	−.135***	−.502***
gender_missing _c	−.094**	−.355***	−.058*	−.263***
age _c	−.005**	−.001	.003*	.004
age_missing _c	.076	.086	−.027	.183**
<i>Order control variables</i>				
purchases _i	n.a.	.824***	n.a.	.895***
year _i	.038**	.044	.065***	.078**
month _{i,2}	−.119	−.247	.070	−.102
month _{i,3}	−.250***	.116	.294***	−.039
month _{i,4}	.026	.217	.196***	−.076
month _{i,5}	.293***	.413**	−.005	−.208
month _{i,6}	.471***	.541***	−.174***	−.021
month _{i,7}	.724***	.181	−.404***	−.434***
month _{i,8}	.428***	−.104	−.156***	−.244*
month _{i,9}	−1.201***	−1.816***	.493***	−.484***
month _{i,10}	−.994***	−1.149***	.488***	−.245*
month _{i,11}	−.487***	−.272	.294***	−.079
month _{i,12}	−.150*	−.185	.243***	−.150
<i>Random effects and spatial autocorrelation</i>				
σ (random effect customer)	.464***	1.088***	.022***	.742***
τ (random effect region)	.114***	.210***	.025***	.226***
λ (spatial auto-correlation)	.599***	.511***	.516***	.518***

Stars indicate whether the 95% (*), 99% (**), 99.9% (***) CI excludes zero.

Table 2.8: Regional influences on online purchasing and returning (per shopping basket) for discounted vs. undiscounted products

DV	discounted products		undiscounted products	
	purchases _i	returns _i	purchases _i	returns _i
Intercept	-4.059***	-5.814***	.354***	-3.128***
$(W \times \text{stores})_r$	.001	-.068	-.009	-.153**
<i>Regional control variables</i>				
$(W \times \text{posts})_r$	-.029	-.113	.036*	-.042
welfare _r	-.039*	-.018	.003	-.006
urbanization _r	.045**	-.094*	-.014	-.055*
cars _r	.092	-.607*	.074	-.294
<i>Customer control variables</i>				
gender_man _c	-.245***	-.845***	.071*	-.449***
gender_missing _c	-.260***	-.440***	.008	-.271***
age _c	.008	-.000	.002	
age_missing _c	.055	.203	-.019	.142*
<i>Order control variables</i>				
purchases _i	n.a.	.940***	n.a.	.775***
year _i	.405***	.278***	-.053***	.055**
month _{i,2}	.489***	.429	-.114*	-.307*
month _{i,3}	1.210***	.642**	-.283***	.009
month _{i,4}	.980***	.601**	-.099*	.033
month _{i,5}	1.076***	.360	-.161***	-.047
month _{i,6}	.493***	.470*	.052	.021
month _{i,7}	.532***	-.458	.161***	-.377***
month _{i,8}	.378***	-.106	.093*	-.287**
month _{i,9}	1.296***	-.010	-.356***	-.406***
month _{i,10}	1.123***	.042	-.169***	-.158
month _{i,11}	.924***	.437	-.196***	-.048
month _{i,12}	1.191***	.295	-.212***	-.125
<i>Random effects and spatial autocorrelation</i>				
σ (random effect customer)	.766***	1.200***	.014***	.736***
τ (random effect region)	.069***	.146***	.013***	.224***
λ (spatial auto-correlation)	.500***	.504***	.501***	.563***

Stars indicate whether the 95% (*), 99% (**), 99.9% (***) CI excludes zero.

2.5.5 Simulation of Effect Magnitude

Table 2.9: Product purchase and return variables

Scenario	Change in no. stores	Description
Moderate store reduction	−109	Closure of one store in each region which has a below-median client/store ratio
Modest store reduction	−51	Closure of one store in each region with a client/store ratio in the lowest quartile
As-is store availability	±0	Actual store availability as observed in the data
Modest store increase	+51	Opening of one store per region, ranked by high to low (prospective) client/store ratio until the same number of stores are opened which were closed in the “Modest store reduction” scenario
Moderate store increase	+109	Opening of one store per region, ranked by high to low (prospective) client/store ratio until the same number of stores are opened which were closed in the “Moderate store reduction” scenario

Translating the coefficient estimates reported above to actual effects sizes is a non-trivial exercise, since the models we use to calculate the effects of store availability on orders and returns are non-linear. Therefore, in this section, we present the results of using partly simulated data to predict the outcome variable in order to find out what change in the number of stores leads to what reduction in returned products per shopping basket. We restrict the prediction to the models where the effect of stores was significant. Therefore, the predictions pertain to the influence of stores on the number of returned products per shopping basket – regarding all products as well as regarding multi-size, higher-priced, and undiscounted products.

The simulation is based on the actual observed data, with the exception of store availability. We base our simulation as closely as possible on the actual data in order to obtain estimates that reflect as closely as possible what would happen in a real-world situation, when changing nothing but store availability. That means we keep almost the entire database used in the analyses intact, but only modify the data on store availability. Next, we predict the outcome variables for each observation using

Figure 2.3: Number of returned products per shopping basket for different product subsets and store availability

the estimation results presented in the previous subsections. A more stylized example would allow for more freedom with regards to the assumed customer, product and regional structure but would also suffer from arbitrariness because many different plausible configurations are conceivable, thus lowering the external validity.

With regards to the store availability variable, we use two scenarios of reducing and two scenarios of increasing store availability – in addition to the as-is scenario of actual observed store availability. We created all scenarios based on what would be plausible from a managerial perspective, i.e., closure of the least promising stores versus opening of most promising stores based on the regional online client-to-store ratio. The underlying rationale is that stores in regions with high online client-to-store ratios will likely have the highest influence on online returns and therefore, it is most beneficial to open such stores first (and close them last). Conversely, stores in regions with low online client-to-store ratios will likely have a small influence on online returns and therefore it is beneficial to close such stores first (and open them last). In order to facilitate comparisons, we use the same (absolute) changes in store numbers for opening and closure scenarios. Table 2.9 lists all scenarios and the associated changes in store availability in detail.

The results of the simulation show that store openings and closures both can have a large effect on product returns (Figure 2.3). The effect sizes greatly depend on how many stores are opened or closed. In general, store openings have a bigger effect on returns than store closures. For example, a modest store increase reduces returns by 2.41%-2.81% while a modest store reduction only increases returns by 1.59%-1.94%. This asymmetric effect results from stores with likely greatest positive influence being opened first (in the opening scenarios) and being closed last (in the closure scenarios). The effect size varies slightly between product subsets with smallest effect sizes for multi-size products and largest effect sizes for undiscounted products. Figure 2.3 provides a detailed account of all effects for each scenario and product subset.

2.5.6 Profit Implications

While the previous simulation results provide insights on the impact of store openings and closures on product returns, they do not yet show us the profit implications. We therefore simulate the individual-customer profit impact of the different store opening and closure scenarios. We calculate this change based on the following components:

1. Return cost per basket, defined as *number of returned products per basket* $\times$ *return processing cost per returned product*.
2. Gross profit per basket, defined as *gross margin* $\times$ *price of an ordered product* $\times$ (*number of ordered products per basket* - *number of product returns per basket*).

3. Profit per customer, defined as $(\text{gross profit per basket} - \text{return cost per basket}) \times \text{number of ordered baskets per customer}$.

We base our calculations on a gross margin of 42.5% (as reported by Damodaran, 2021), and a return processing cost of €3 to €12, based on interactions with practitioners from online retailing. We use the profit per customer in the existing situation as benchmark, and determine the percentage change relative to the benchmark scenario. Figure 2.4 provides a detailed overview of the outcomes for the different scenarios and return processing costs

Figure 2.4: Profit impact of store reductions and increases for different return processing costs

The results show that store openings have a clear beneficial effect on individual-customer profitability. Not surprisingly, this effect is stronger when return processing costs are higher. Moderate store increases could then increase the individual-customer profitability with over 1.6% (processing cost of €12) compared to the existing situation. A same-size decrease in the number of stores, however, would result in a decrease of the individual-customer profitability with over 1%. In the world of online retail, where net profits are often small (if any), these changes, while small, can make the difference for the retailer.

One extreme decision the retailer could envision, is abandoning its existing offline stores to become a pure online retailer. Our simulations show that such decision would have a clear detrimental effect on its online operations, as it would increase the number of returns with no less than 15.65%, thereby reducing the individual-customer profitability with 5.15%. Such decision should consequently not be taken easily.

2.6 Discussion

2.6.1 Summary of Findings

In this paper, we studied the effect of physical, offline, retail stores on the number of product purchases and product returns by customers in the retailer's online channel. The results are partly in line with what we predicted (Table 2.10).

Our key result is that offline retail stores are in no case harmful and in some cases actually beneficial to the online channel. More specifically, the presence of offline retail stores is not harmful to the online channel as it does not decrease the number of products purchased online: it does not significantly affect the number of purchased shopping baskets per customer nor the number of purchased products per shopping basket. Theory indicates two possible mechanisms through which physical, offline, stores could influence online product purchases: by detracting customers from the online channel due to channel substitution (e.g., Neslin & Shankar, 2009), and by attracting customers to the online channel due to cross-channel promotion (Mitra & Fay, 2010). Our findings suggest that both effects are rather small and/or stay in balance.

Besides physical stores not being harmful, their presence can in fact be helpful, as it significantly decreases the number of returned products per shopping basket. This overall pattern, in addition, appears to be most outspoken for products that show a higher perceived risk for customers. These findings are in line with what we theorized. Customers appear to anticipate the risk of needing to return and adapt their purchase behavior, especially for higher-risk products (Janakiraman & Ordóñez, 2012; V. W. Mitchell, 1992). They thus seem to engage in show-rooming for those higher-risk products in order to avoid product returns (Neslin & Shankar, 2009). Products with multiple sizes, a higher price or no discount have a higher perceived risk for customers than uni-size, lower-priced or discounted products. It should therefore not come as a surprise that for the former types of products, physical, offline, stores do reduce product returns whereas for the latter, lower risk, products, offline stores have no significant effect. We find no empirical evidence for an increase in product returns, which could have been fueled by the decreased hassle or cost of actually returning a product (Kim & Wansink, 2012).

Findings of prior research regarding the influence of offline stores on the online

Table 2.10: Overview of the main findings

Hypothesis	Findings
H1a Offline channel presence decreases the number of ordered shopping baskets.	Not supported
H1b Offline channel presence increases the number of ordered shopping baskets.	Not supported
H2a Offline channel presence decreases the number of purchased products per shopping basket.	Not supported
H2b Offline channel presence increases the number of purchased products per shopping basket.	Not supported
H3a Offline channel presence decreases the number of returned products per shopping basket.	Supported
H3b Offline channel presence increases the number of returned products per shopping basket.	Not supported
H4a The impact of offline channel presence on the number of purchased products per shopping basket is more negative/less positive for products with higher fit uncertainty compared to products with lower fit uncertainty	Not supported
H4b The impact of offline channel presence on the number of purchased products per shopping basket is more negative/less positive for higher-priced products compared to lower-priced products	Not supported
H5a The impact of offline channel presence on the number of returned products per shopping basket is more negative/less positive for products with higher fit uncertainty compared to products with lower fit uncertainty	Supported
H5b The impact of offline channel presence on the number of returned products per shopping basket is more negative/less positive for higher-priced products compared to lower-priced products	Supported
H5c The impact of offline channel presence on the number of returned products per shopping basket is more negative/less positive for undiscounted products compared to discounted products	Supported

channel are mixed. Pauwels and Neslin (2015) find that adding physical stores does not cannibalize purchases in the online channel. Avery et al. (2012), in turn, find that adding physical stores does not influence purchases in the online channel in the short run, but does increase them in the long run. Our findings are consistent with the findings by Pauwels and Neslin (2015), as we find no evidence for a difference in online purchases due to a higher offline store presence. A reason for the difference in findings compared to the study by Avery et al. (2012) might be that the retailer in our study is large and well-known so that stores did not increase brand awareness, which was suggested as an explanation for the positive effect in their study. If there would be a positive effect of offline stores on online orders, it would in fact strengthen the notion that stores are helpful and not harmful to the online channel.

Regarding product returns, Pauwels and Neslin (2015) find that adding physical stores does increase the total return frequency. Their findings, however, are across all channels, and do not distinguish between returns of products purchased online versus offline. As a consequence, it is not possible to directly compare our study with their study. Besides, one explanation of the difference might be the higher number of nearby stores in our study. When the retailer has an offline channel but stores are very distant, stores might be attractive enough for customers to use for returning but not attractive enough to use for casual show-rooming, thus fostering returns instead of averting them.

Our study is the first to investigate the influence of the offline channel on purchases and returns in the online channel which distinguishes between effects for products with different risk perceptions for the customer. Our findings show that the investigated risk-perception driving product characteristics are a decisive factor for offline-on online-channel influence, and that neglecting them masks an important aspect in the relationship between both channels. Furthermore, we developed a statistical model that takes the regional nature of stores into account and showed that the estimation of a spatial model in this case is feasible, even for a large number of regions. By that, we contribute to prior research on channel interactions both substantially as well as methodologically.

2.6.2 Managerial Implications

Over the course of the last decades, customers begun to shop more and more online, which led to the rise of e-commerce companies such as Amazon and the creation of online channels by traditional retailers such as Wal-Mart. The increasing importance of the online channel poses the question whether the offline channel is still beneficial to maintain (or further develop) – or whether it harms the retailer’s performance. Our findings indicate that online performance is not harmed, as online sales are not significantly lowered by the presence of an offline store. Instead, physical, offline,

stores decrease returns and thereby help to increase the performance of the online channel, which often suffers from high return rates (Ofek et al., 2011).

The usefulness of physical stores, however, depends on the retailer's profile and strategy. The retailer's assortment determines how much overall reduction of product returns in the online channel can be expected. The higher the risk of non-fit for the customer or the more expensive the products on display are, the more returns are reduced. That means retailers, which sell higher price products, products without many discounts and products which have personal fit requirements, stand to benefit the most from physical retail stores.

Furthermore, our simulation shows that effects of small increases and decreases in the number of stores are asymmetric, with an increase in stores leading to a stronger reduction in returns compared to the increase in returns that results from a similar reduction in the number of stores. This indicates that retailers likely benefit from accounting for online customer locations when setting store locations. While a small reduction in the number of – from the point of view of the online channel: unappealing – stores, as a consequence, may not harm the retailer much with regard to product returns, a small increase in the number of – from the point of view of the online channel: appealing – stores will help more. Besides, increasing store availability shows diminishing returns, i.e., adding a few stores has a higher average per-store effect on product returns than adding many stores. That means that retailers stand to gain most, per-store, by the first additional store openings.

Overall, the decision to which degree physical stores should be maintained depends on many factors. Maintaining stores comes at a substantial cost and managers need to take the actual sales and cost of the offline channel into account. To have an unbiased whole picture, however, managers should also take into account the beneficial effect of physical stores on returns in the online channel, depending on store profile.

2.6.3 Limitations and Further Research Directions

In our research, we use online data from a fashion retailer. Performance risk is very pronounced in the fashion sector and therefore, this sector is well-suited to study the moderating role of risk in the influence of physical stores on online purchases and returns. Furthermore, clothes and sports goods are the most popular product category for online purchases, before household goods, various media products (books, films, games) and electronic equipment (Eurostat, 2011a). In spite of the concrete product category, the underlying mechanism of how physical stores influence the online channel should equally apply to retailers in various sectors. Depending on the respective product characteristics and risk profile, the influence of physical stores is likely to be more or less pronounced. For example, household goods such as furniture usually have a high price and so the effect of physical stores on returns in the online

channel might be even greater. A future study could examine the effect of physical stores on purchases and returns for other product categories.

In addition, we focus our analysis on the within-firm influence of the offline channel on online shopping behavior since firms can directly influence the existence of their own stores. Nevertheless, there could be cross-firm cross-channel influences. Usually, higher switching costs, lock-in effects – sometimes voluntarily set up such as loyalty programs (Bijmolt & Verhoef, 2017) – and assortment differences impede customers from switching easily from one firm to another (Brynjolfsson et al., 2013; Lemon & Verhoef, 2016). In spite of this, one could imagine e.g., a cross-firm category promotion effect. In sum, a future study could investigate the influence of competitor store presence on online purchase and return behavior.

Stores might also have a more or less pronounced promotional and trust-building effect, depending on the retailer. Due to this, we theorized that physical stores could actually increase online sales. While we found no significant effect, this might be due to the fact that our data comes from a large and well-known retailer. In contrast, for smaller and less well-known retailers, this effect might play a role in fostering online purchases (Avery et al., 2012). A future study could investigate different retailers and find out under which conditions such a cross-channel promotion effect exists.

The current setup makes abstraction of the focal retailer's as well as competitors' marketing actions for both the online and offline channels. Such actions include for example the assortment offered, advertising effort, as well as applied pricing strategies. A future study could investigate the impact of both the effort of a single retailer in the online relative to the offline channel, and the relative competitive effort of a retailer in the online and/or offline channel on customers' online purchasing and returning behavior.

Finally, our research took a retailer focus, and concentrated on overall insights on factors retailers can influence. However, taking a consumer focus, an in-depth investigation on the extent to which observed overall effects depend on consumers' shopping motivations and personality traits could provide valuable insights on how things can be different at the individual-consumer level, thus adding to our understanding of consumers' multichannel shopping and returning behavior.

3

The Influence of Fixed-Fee and Threshold-Based Free Shipping on Online Orders and Returns

Online retailers can recoup part of the relatively high logistics cost by instating a shipping policy which includes shipping fees on some or all of the orders. This paper compares two wide-spread shipping policies: fixed-fee shipping and threshold-based free shipping. It contrasts both policies' influence on sales – aggregate as well as decomposed into order value and order count – and returns. Regarding the latter, the paper investigates whether filler purchases – purchases that make the order surpass the required threshold value for threshold-based free shipping – explain contrasting return quotas. Insights are based on the analysis of a unique database from a major European online retailer containing 26.21 million orders of 83.79 million items from 3.81 million customers and covering a broad range of product categories. Results show that threshold-based free shipping leads to substantially higher overall sales and more orders, while fixed-fee shipping leads to less returns, even though the effect is not driven by filler purchases. Finally, a simulation shows that the positive effects (on orders) of threshold-based free shipping likely outweigh the negative effects (on product returns) under most conditions.

3.1 Introduction

Online retailing has grown heavily over the last two decades. While online retailers do save on rent compared to traditional brick-and-mortar stores, they incur new logistical costs. Every shipped and returned order needs to be handled separately, threatening to make logistics costly (Bijmolt et al., 2019; Caro et al., 2020). A popular way to recover (part of) this cost for retailers is to make customers pay a shipping fee. A shipping fee increases the price that customers have to pay for an order online, and usually is either a fixed fee or a fee that increases or decreases in steps. Such fixed or variable shipping fees may incentivize differing purchase and return behaviors (Lewis, 2006; Shehu et al., 2020). As retailers strive to maximize orders while keeping returns low (Minnema et al., 2018; Petersen & Kumar, 2015) and customers are particularly reluctant to pay for shipping fees (Smith & Brynjolfsson, 2001), the choice of shipping fee policy should be taken with care.

The differences between paid shipping policies are under-researched, in spite of recent managerial interest (Retail Detail, 2019), and no paper so far investigates the consequential difference in returns, even though returns are crucial for profitability. In this paper, we contrast two exemplary and widely used shipping fee policies: fixed-fee shipping and threshold-based free shipping, i.e. shipping fees that are waived for bigger orders (e.g., Lewis, 2006). Thus, we contribute to prior research, notably by Lewis (2006) and, more recently, by Lepthien and Clement (2019) and Sahoo et al. (2018), by comparing two different paid shipping policies with regards to both orders and returns.

In the remainder of the paper, we first reason why customers are motivated to order and return more with a threshold-based free shipping policy, and why it additionally may lead to strategic behavior, i.e., customers ordering additional goods to reach the free-shipping threshold. Those so-called filler purchases might either be to the benefit or detriment of the retailer, depending on their return rate (Minnema et al., 2018). Next, we conduct an empirical analysis using data from a large European online retailer, which recently changed its shipping policy from fixed-fee to threshold-based free shipping. Our findings show that threshold-based free shipping does influence sales and the number of orders, and substantively changes return rates. While the return rate in general is higher, filler purchases are returned less rather than more compared to regular purchases. In a post-hoc analysis, we further investigate such filler purchases and reasons why they are returned less.

3.2 Theoretical Background

3.2.1 Research Framework

A shipping fee is a mark-up on the price of an order to get the products delivered at home. Depending on the shipping policy, this mark-up is a fixed fee (independent of the order) or it is determined by characteristics of the order (like its value). For example, an order of a book at €10 and a jacket at €100 might both have a shipping fee of €2.50 with a fixed-fee policy, or of €5 and €0, respectively, with a threshold-based free shipping policy, a policy whereby shipping cost is waived when the order value surpasses a certain threshold (e.g., €20 in this case). In addition, as the order size varies, the relative price increase per product varies, too. In the example above, a shipping fee of €2.50 for a €10 book means a price increase of 25% whereas a shipping fee of €2.5 for a €100 jacket only means a price increase of 2.5% (Hess et al., 1996). This sort of price is a so-called partitioned price, with a fixed partition (the original product price) and a variable partition (the price increase due to shipping cost). Customers are very sensitive to variable price partitions, especially in the case of shipping fees (Hamilton & Srivastava, 2008; Smith & Brynjolfsson, 2001).

In our research, we will focus on the difference between fixed fee shipping and a threshold-based free shipping. The defining difference is that with threshold-based free shipping, the shipping fee is waived for large orders. This difference, however, leads to different incentives with regards to overall order amount (i.e., sales), order frequency, the value of each order, and the return probability. As the research framework in Figure 3.1 shows, we expect a range of effects based on that difference, which we will explain in detail in the next sections.

3.2.2 Embedding into Prior Research

Our paper positions itself in a stream of empirical work, which compares the effects of different elements of shipping policies. Most research focuses on the effect of shipping fees on orders (e.g., Lewis, 2006; Lewis et al., 2006) but recently, three papers have integrated product returns into the analysis (Lepthien & Clement, 2019; Sahoo et al., 2018; Shehu et al., 2020). Table 3.1 provides an overview of the main findings of prior work. Previous research focused either on free shipping and its difference to other shipping policies or on parameters within one shipping policy. Little is known concerning the differences between two paid shipping policies. Therefore, this paper contributes to the stream of literature as it is the first to contrast the consequences of a threshold-based free-shipping policy with those of a fixed-fee shipping policy on multiple outcome variables. This wide array of dependent variables allows us to not only predict atomic effects concerning one outcome but also to realistically compare two shipping policies in their overall effect.

Table 3.1: Prior research regarding shipping fees

Paper	DV	IV	Relationship
<i>order-related dependent variables</i>			
Lewis (2006)	Order frequency	Shipping fee	—
Lewis et al. (2006)	Order frequency	Free shipping (vs. threshold-based free shipping)	+
Lepthien and Clement (2019)	Order frequency	Free shipping threshold	—
Shehu et al. (2020)	Order frequency	Free shipping (vs. fixed-fee shipping)	+
Lewis (2006)	Order value (before returns)	Penalizing larger orders	—
Lewis (2006)	Order value (before returns)	Penalizing smaller orders	+
Lewis et al. (2006)	Order value (before returns)	Free shipping (vs. threshold-based free shipping)	—
Lepthien and Clement (2019)	Order value (before returns)	Shipping fee	+
Lepthien and Clement (2019)	Order value (after returns)	Shipping fee	+
Shehu et al. (2020)	Ordering of riskier products	Free shipping (vs. fixed-fee shipping)	+
<i>return-related dependent variables</i>			
Shehu et al. (2020)	Return probability	Free shipping (vs. fixed-fee shipping)	+
Sahoo et al. (2018)	Return probability	Order value < \$5 above free shipping threshold	—
Lepthien and Clement (2019)	Return probability of “strategic returns”	Free shipping threshold	+

Figure 3.1: Research Framework: Expected effects of shipping policy

Effects on Product Orders

Prior research shows that customers adapt how they order as a response to different shipping fees incentives Table 3.1. Higher shipping fees correlate with reduced ordering, while fees penalizing a certain order size lead to a different order size (Lewis, 2006). Comparing concrete policies, free shipping leads to smaller and more frequent orders than threshold-based free shipping (Lewis et al., 2006) and, in line with that, also more frequent orders than fixed-fee shipping (Shehu et al., 2020). For threshold-based free shipping, a higher threshold leads to less orders (Lepthien & Clement, 2019). In addition to all aforementioned aggregate effects, shipping policies may also change what customers order: Shehu et al. (2020) find that customers tend to purchase more products that are difficult to evaluate online with free shipping.

Effects on Product Returns

Prior research also shows that customers adapt how they return products as a response to different shipping fees incentives – although insights are more limited. Free shipping leads to more returns than fixed-fee shipping (Shehu et al., 2020). Threshold-based free shipping has been argued to lead to more returns due to strategic order and return-behavior (Lepthien & Clement, 2019). Conflicting with that proposition is that threshold-based free shipping has been shown to lead to less returns for orders

just above the free shipping threshold (Sahoo et al., 2018).

3.2.3 Hypotheses

The Influence of Shipping Fees on Orders

There are two reasons, why we expect that fixed-fee shipping leads to lower sales than threshold-based free shipping. First, with a fixed-fee shipping, the customer has to pay the shipping fee for every order, regardless of order value, whereas with a threshold-based free shipping, the shipping fee is waived for large orders. In other words, shipping is potentially free and on average cheaper with threshold-based free shipping than with fixed-fee shipping. In general, higher cost leads to less demand, since price elasticity is usually negative (Bijmolt et al., 2005). In particular, shipping fees have been found to be even more influential than regular price (Lewis, 2006; Smith & Brynjolfsson, 2001). Thus, we expect that fixed-fee shipping leads to less sales overall than threshold-based free shipping due to higher average costs for the customers.

Second, with fixed-fee shipping, the more individual orders customers make, the more shipping fees they have to pay. This incentivizes customers to distribute the same product purchases among fewer orders, as this allows them to economize on shipping fees. A practical way to do so is, to accumulate planned purchases by postponing them (which customers are willing to do to save money, see e.g., Greenleaf & Lehmann, 1995). We therefore expect customers to postpone purchases with fixed-fee shipping. Postponement of purchases, in turn, can lead to abandonment of purchases, e.g., because preferences change (Stigler & Becker, 1977) or because the purchase was made somewhere else in the meantime. Abandoned purchases, in turn, have a detrimental effect on sales. The situation is different for threshold-based free shipping: here, more orders do not generally equal more shipping fees and customers have no incentive to postpone purchases beyond reaching the free shipping threshold. Thus, we expect less abandoned purchases resulting in a less detrimental effect on sales. Therefore, when comparing both policies, we expect fixed-fee shipping to lead to less sales than threshold-based free shipping. In sum, both arguments lead to the following hypothesis:

- H₁ Threshold-based free shipping leads to higher sales compared to fixed-fee shipping.

Fixed-fee shipping may incentivize customers to delay purchases in order to distribute them among (a) fewer and (b) larger orders and, thereby, reduce the total of due shipping fees. For threshold-based free shipping, on the other hand, this is true

only to a limited extent. Once the order size is above the free shipping threshold, postponing and combining orders does not further reduce total shipping costs. Therefore, threshold-based free shipping only provides a constrained incentive for combining smaller into larger orders – until the free shipping threshold is reached – whereas fixed-fee shipping provides an unconstrained incentive for combining smaller into larger orders – because the higher the purchase value, the lower the relative weight of the shipping fee. This results in the following two hypotheses:

- H2 Threshold-based free shipping leads to more orders compared to fixed-fee shipping.
- H3 Threshold-based free shipping leads to a lower average order value compared to fixed-fee shipping.

The Influence of Shipping Fees on Returns

Fixed-fee shipping results in every order having to pay a shipping fee whereas threshold-based free shipping results in many orders not having to pay a shipping fee. Having to pay a non-refundable fee more often will lead to less returns for two reasons. The first reason is similar irrational behavior as in comparable situations with sunk cost. When customers decide to return their order, they have to write off the money spent on shipping fees. Instead, they have a tendency to continue on their path, once an investment has been made, even if it results in financially detrimental outcomes (Carter et al., 2007; Domeier et al., 2018). We expect customers to consider shipping fees as money wasted when returning and therefore expect them to return less with fixed-fee shipping, where shipping is always paid, than with threshold-based free shipping, where shipping is regularly free. The second reason for expecting less returns due to a non-refundable shipping fee is economic customer behavior due to costly re-ordering. Customers might decide to return a product, if a product does not fully align with their preferences, and re-order another one. However, the benefit of returning and re-ordering has to outweigh the cost (Anderson et al., 2009; Petersen & Kumar, 2015), which is increased by having to pay shipping fees. Therefore, if the ordered new product has only a slight advantage over the returned old product, having to pay additional shipping fees might render the exchange unattractive. Since fixed-fee shipping always results in shipping fees and threshold-based free shipping does not, fixed-fee shipping more often renders returning unattractive in such cases. In sum, based on both explanations, we expect that:

- H4 Threshold-based free shipping leads to more returns compared to fixed-fee shipping.

Shipping fees might also influence what customers return. Threshold-based free shipping is free when ordering above the threshold. Hence, as long as the order size is below the threshold, customers have to compromise between paying the shipping fee or paying more for the order itself – by ordering more. When the customer chooses the latter option and orders an additional product in order to surpass the free-shipping fee threshold, we call this purchase a “filler” purchase. Thus, we define a filler purchase as a purchase that was added to the shopping basket at the end of the shopping trip, with the order value without it being below the free shipping threshold and with it being above the free shipping threshold. From a theoretical point of view, such filler purchases could be returned both less often than “regular”, i.e., non-filler purchases – or more often, and we formulate opposing hypotheses about the effect.

On the one hand, customers have the possibility of economizing their purchase behavior by adding a product to their order, which they can anticipate to purchase anyway in the future, such as regularly purchased goods (e.g., beauty or sanitary products). Customers can perceive such additional purchase as a smart bargain, because they spend their money on a product instead of on shipping costs. Customers are prone to bargain hunting, which is the biggest source of enjoyment in brick-and-mortar retail shopping (Cox et al., 2005), especially when they perceive their own action as responsible for the lowered price (Schindler, 1989). If customers add regularly purchased goods to their order, returns of these purchases are likely lower, since familiar purchases are returned less than unfamiliar purchases (Petersen & Kumar, 2009).

H5a Threshold-based free shipping leads to less returns of filler purchases compared to regular purchases.

There are also reasons for which filler purchases might be returned more often. First, customers might intentionally plan to order and return a filler purchase and only order the filler purchase to save shipping cost with a higher order value. Previous research shows that customers are known to strategically abuse retailer policies for their personal gain (Wachter et al., 2012) and this case provides a tangible gain without any risk. Customers could extend their order by any random product, provided it lets the order surpass the free shipping threshold, and thereby save out the shipping fee. A second, unrelated, explanation for higher returns of filler purchases is that customer might decide spontaneously to order more when confronted with the threshold-based free shipping. In this case, however, the resulting filler purchases are unplanned purchases, which, being more likely to be regretted post-purchase (Saleh, 2012) and therefore, have a higher return probability. In sum, we therefore hypothesize that:

H5b Threshold-based free shipping leads to more returns of filler purchases compared to regular purchases.

3.3 Data

For this study, we have access to a unique dataset from a major European online retailer. The dataset contains 26.21 million orders of 83.79 million items from 3.81 million customers in a three years period (from July, 2016 to June, 2019). The assortment of the retailer is broad and consists of, among others, fashion, furniture, electronics, and toys. Fashion has the largest share, reflecting its popularity in e-commerce overall (Eurostat, 2021a), but other product categories are far from insignificant in terms of economic value. Figure 3.2 shows the distribution of orders among the retailer’s product categories.

Figure 3.2: Distribution of purchased products among categories

On the 2nd of November, 2016, the retailer changed its shipping policy from fixed-fee shipping with fees depending on the product category (e.g., €0 for laptops and printers, €1.95 for DVDs and software, and €5.95 for fashion and small domestic appliances, among others) to threshold-based free shipping with a unified €2.95 shipping fee and a free-shipping threshold of €20. The retailer continued to charge no additional cost for shipping of product returns.

3.3.1 Datasets and Variables

For our analyses, we use two datasets. Table 3.2 presents an overview of the datasets and variables used in our empirical study. The first dataset is at the daily level and contains variables related to the online retailer’s sales. Here, we focus on three dependent variables: sales, order count, and order value, all on a daily level. The focal

independent variable for these analyses at the daily level is an indicator variable for threshold-based free shipping that allows us to compare the effect of threshold-based free shipping with fixed-fee shipping. Besides, we include a range of control variables for weekday, month, and year. Since the firm unified shipping fees across categories when introducing threshold-based free shipping – resulting in an increased fee for some orders and a decreased fee for others – we group orders according to the direction of shipping fee change. As a result, we have two time-series, one for each group of orders.

The second dataset is at the product-purchase level and contains variables related to the product returns. The dependent variable “returned” indicates whether or not an individual purchase was returned. Analyzing returns at the product-purchase level allows us to provide insights both at the product level – the impact of purchase type (whether or not the product is a filler purchase) and shipping fee change – and at the order level – whether or not the order was placed with a fixed-fee or threshold-based free-shipping policy. We also control for other aspects at the product level – price and product category –, at the order level – discounts, order size, and whether or not the product was the last in the order, as well as day, month, and year of the order – and at the customer-level – age, gender, and the length of the customer relationship.

3.3.2 Model-free Insights

Over-time plots of daily order and return variables (Figure 3.3) indicate seasonal variation plus an additional shift of the average of each variable from the period with fixed-fee shipping to the period with threshold-based free shipping. In line with our hypotheses, threshold-based free shipping seems to increase daily sales, the number of orders, and decrease order value in comparison with fixed-fee shipping. Specifically, the mean daily value of all sales is €2.57m for fixed-fee shipping and €3.27m for threshold-based free shipping (+€.70m); the daily number of all orders is 17 313 for fixed-fee shipping and 24 786 for threshold-based free shipping (+7473); the average order size of all orders is €148.12 for fixed-fee shipping and €132.22 for threshold-based free shipping (-€15.9); and the daily percentage of returned products is 43% with fixed-fee shipping and 45% with threshold-based free shipping. Hence, in general, the model-free evidence tends to support our hypotheses, but it does not control for other explanatory factors, so we continue with more detailed analyses of the data.

3.4 Methodology

We employ two sets of models: the first to analyze daily-level sales outcomes, i.e., sales value, order count, and order value, and the second, to analyze product-purchase level product returns.

Table 3.2: Dependent and independent variables used in the analysis

Variable	Definition	Summary
<i>Dataset: Day level (n = 2188)</i>		
$\text{sales}_{t,g}^3$	Sales at day t (for orders in group g)	g = shipping fee up avg: 2 946 583 avg: 243 511
$\text{ordercount}_{t,g}^3$	Count of orders at day t (for orders in group g)	avg: 1 000 423 (sd: 103 020) avg: 21 603.28 (sd: 1039.89)
$\text{ordervalue}_{t,g}$	Average order value at day t (for orders in group g)	avg: 137.16 (sd: 13.75) avg: 106.92 (sd: 20.810)
shippingpolicy_t	Whether threshold-based free shipping is valid at day t (1), or not (0)	0: 11.32%, 1: 88.68%
$\text{day}_{\text{day},t}^1$, $\text{month}_{\text{month},t}$, and $\text{year}_{\text{year},t}$	Whether (1) or not (0) day t is Monday, Tuesday, etc. / in 2017, 2018, or 2019	see Figure 3.3
<i>Dataset: Product-purchase level (n = 83 704 086)</i>		
returned_p	Whether product p is returned (1), or not (0)	0: 55.23%, 1: 44.77%
shippingpolicy_p	Whether the product p was ordered on the threshold-based free shipping policy (1) or on a fixed-fee shipping policy (0)	0: 8.52%, 1: 91.48%
regular_p / filler_p	Whether product p is added to the order after all other products and lifts the shopping basket from below the free-shipping threshold to above it ($\text{filler}_p = 1$), or not ($\text{regular}_p = 1$)	regular_p : 97.51% filler_p : 2.49%
fee_up_p / fee_down_p	Whether product p 's category shipping fee increased ($\text{fee_up}_p = 1$) or decreased with the shipping policy change ($\text{fee_down}_p = 1$)	fee_up_p : 7.05% fee_down_p : 92.95%
price_p^1	Product price of product p	avg: 42.81€ (sd: 69.25€)
category_p	The category of product p	see Figure 3.2
discounted_p	Whether product p has a discounted price when purchased (1), or not (0)	0: 53.61%, 1: 46.39%
basketsize_p^2	Count of products ordered together with product p	avg: 7.06 (sd: 7.00)
lastinbasket_p	Whether product p is added to the order after all other products (1), or not (0)	0: 68.71%, 1: 31.29%
$\text{day}_{\text{day},p}^1$, $\text{month}_{\text{month},p}$, and $\text{year}_{\text{year},p}$	Whether (1) or not (0) product p is purchased on Monday, Tuesday, etc. / in February, March, etc. / in 2017, 2018, or 2019	see Figure 3.3
age_p^1	Age of the customer of product p	avg: 42.91 (sd: 11.28)
$\text{gender}_{\text{male},p}^1$	Whether gender of the customer of product p is female (0) or male (1)	0: 83.18%, 1: 16.82%
cvel_years_p^1	Length of patronage of the customer of product p in years	avg: 10.22 (sd: 8.84)

To obtain a plausible baseline estimate, variables before estimation are: ¹ mean-centered, ² subtracted by one, ³ on the (natural) logarithmic scale.

Figure 3.3: Daily sales, order counts, order values, and return percentages

3.4.1 Analyzing Sales, Order Count, and Order Value

For sales, order count, and order value, we use data at a daily level. This allows us to identify the effect of the introduction of threshold-based free shipping while controlling for seasonal effects. We analyze the daily data using cross-sectional time-series regression models (StataCorp, 2020). We account for changing shipping fees by fixed-effects and estimating the effect of threshold-based free shipping separately for the group of orders with increasing and decreasing shipping fees. Besides, we control for day of week, month, and year. In addition, we allow for autocorrelation in the error term. We estimate the same model (3.1) for all time-dependent outcome variables: daily sales, order count, and order value:

$$y_{g,t} = \alpha + \beta_{1,g} sp_{g,t} + \sum_{i=2}^{21} \beta_i x_{i,t} + v_g + \varepsilon_{g,t}, \quad (3.1)$$

with: $\varepsilon_{g,t} = \rho \varepsilon_{g,t-1} + \eta_{g,t}$, $g \in \text{up, down}$, $t \in 0, 1, \dots, 1094$,
for $y_{g,t} \in \text{logged sales, logged order count, order value}$

where t is the day, g is the group of orders (with “up” consisting of orders with increasing and “down” consisting of orders with decreasing shipping fees) which accounts for an upward or downward change of the shipping fee per category resulting from the unification of shipping fees across categories with the introduction of threshold-based free shipping, $sp_{g,t}$ is an indicator variable for shipping policy at day t of group g (with threshold-based free shipping = 1, fixed-fee shipping = 0), $x_{i,t}$ with $i = 2, 3, \dots, 21$ are the control variables for year¹, month, and weekday, v_g is the group fixed effect, and $\varepsilon_{g,t}$ is the error term. We apply a log-transformation to the dependent variables to deal with the long right-hand tail and make the distribution more symmetric and Normal.

3.4.2 Analyzing Returns

Base Model

For product returns, we use data at the product-purchase level. This allows us to control for the effect of purchase type (i.e., filler and regular purchases) and other purchase-, product- and customer-level variables. To assess our hypothesized effects on the binary dependent variable product return, we use three binomial logit regression models. First, we start by estimating the influence of shipping policy on product

¹ To address concerns about multicollinearity between year, month, and shipping policy indicator variables, we also estimated the model with a linear effect for years. Parameter estimations were practically identical.

returns in general, and compare returns with threshold-based free shipping to returns with fixed-fee shipping. We control for whether the product belongs to the group with increasing or decreasing shipping fees and include the interaction of this factor with threshold-based-free shipping indicator. Additionally, we control for a range of additional purchase-level variables. This is our base model for product returns (3.2):

$$\begin{aligned} \text{logit}(\text{returned}_p) = & \alpha_{\text{up}} \text{fee_up}_p + \alpha_{\text{down}} \text{fee_down}_p \\ & + \beta_{1,\text{up}} \text{sp}_p \times \text{fee_up}_p + \beta_{1,\text{down}} \text{sp}_p \times \text{fee_down}_p \\ & + \sum_{i=2}^{44} \beta_i x_{i,p} + \varepsilon_p \end{aligned} \quad (3.2)$$

where p is the product purchase, sp_p indicates shipping policy as before, fee_up_p and fee_down_p denote whether the shipping fee increased or decreased, $x_{i,p}$ are the control variables for year, month, weekday, and product category, and ε_p is the error term.

Return Probability for Filler versus Regular Purchases

Second, we extend our base model by indicators for the type of product purchase, i.e., whether it is a regular or a filler purchase. In the resulting model, we compare the baseline return probabilities (under fixed-fee shipping) with the return probabilities of filler and regular purchases under threshold-based free shipping. The extended model is:

$$\begin{aligned} \text{logit}(\text{returned}_p) = & \alpha_{\text{up}} \text{fee_up}_p \\ & + \alpha_{\text{down}} \text{fee_down}_p \\ & + \beta_{1,\text{up}} \text{sp}_p \times \text{fee_up}_p \times \text{filler}_p \\ & + \beta_{2,\text{up}} \text{sp}_p \times \text{fee_up}_p \times \text{regular}_p \\ & + \beta_{1,\text{down}} \text{sp}_p \times \text{fee_down}_p \times \text{filler}_p \\ & + \beta_{2,\text{down}} \text{sp}_p \times \text{fee_down}_p \times \text{regular}_p \\ & + \sum_{i=3}^{45} \beta_i x_{i,p} + \varepsilon_p \end{aligned} \quad (3.3)$$

where the variables are defined similarly to before and we include an additional indicator for whether product p is a filler purchase or regular purchase (denoted by filler_p and regular_p).

Third, as a control for the findings of the second model, we estimate the effect of threshold-based free shipping as well as fixed-fee shipping on returns of both purchase types. In particular, we proceed by splitting coefficients α_{up} and α_{down} of model

(3.3) into two coefficients each ($\alpha_{1,up}$, $\alpha_{2,up}$ and $\alpha_{1,down}$, $\alpha_{2,down}$) – for distinguishing filler from regular purchases with fixed-fee shipping. By doing so, we obtain

$$\begin{aligned}
 \text{logit}(\text{returned}_p) = & \alpha_{1,up}(1 - \text{sp}_p) \times \text{fee_up}_p \times \text{filler}_p \\
 & + \alpha_{2,up}(1 - \text{sp}_p) \times \text{fee_up}_p \times \text{regular}_p \\
 & + \alpha_{1,down}(1 - \text{sp}_p) \times \text{fee_down}_p \times \text{filler}_p \\
 & + \alpha_{2,down}(1 - \text{sp}_p) \times \text{fee_down}_p \times \text{regular}_p \\
 & + \beta_{1,up}\text{sp}_p \times \text{fee_up}_p \times \text{filler}_p \\
 & + \beta_{2,up}\text{sp}_p \times \text{fee_up}_p \times \text{regular}_p \\
 & + \beta_{1,down}\text{sp}_p \times \text{fee_down}_p \times \text{filler}_p \\
 & + \beta_{2,down}\text{sp}_p \times \text{fee_down}_p \times \text{regular}_p \\
 & + \sum_{i=3}^{45} \beta_i x_{i,p} + \varepsilon_p
 \end{aligned} \tag{3.4}$$

where $1 - \text{sp}_p$ is the reverse of indicator variable sp_p (i.e., having fixed-fee shipping = 1 and threshold-based free shipping = 0).

Model (3.4) has as a full factorial design for shipping policy (threshold-based free shipping versus fixed-fee shipping) and purchase type (filler purchase versus regular purchases). The further distinction between purchase types allows us to contrast “real” filler purchases (i.e., goods that comply with the filler purchase definition and are purchased with threshold-based free shipping) with purchases that are fully alike filler purchases without being actual filler purchases (i.e., goods that comply with the filler purchase definition but are purchased with fixed-fee shipping).

3.5 Results

3.5.1 Influence of Shipping Fee on Sales, Order Frequency, and Order Value

First, we find that threshold-based free shipping significantly increases daily sales, considering the group of orders where the shipping fees decreased (model 3.1a in Table 3.3). The increase is large with an effect size of .373 in logged sales ($p < .001$) or, by exponentiating the coefficient, 45.21% in non-logged sales. The effect of threshold-based free shipping is not significant for the group of orders where the shipping fee increased. The difference in effect between both groups suggests that an increase in shipping fee alone would have a negative effect on sales which is countered by threshold-based free shipping. In sum, we have partial evidence in support of H1,

Table 3.3: Influence of threshold-based free shipping on sales, order count, and order value

Dependent variable:	log of sales (3.1a)	log of order count (3.1b)	order value (3.1c)
Constant	13.613*** (.019)	8.643*** (.019)	142.397*** (.950)
threshold-based free shipping _{shipping fee up}	-.057 (.089)	-.020 (.089)	-3.298 (4.530)
threshold-based free shipping _{shipping fee down}	.373*** (.089)	.361*** (.089)	-2.665 (4.530)
year ₂₀₁₇	-.040 (.067)	.051 (.067)	-9.865** (3.409)
year ₂₀₁₈	-.201** (.069)	.008 (.068)	-22.789*** (3.489)
year ₂₀₁₉	-.166* (.080)	.118 (.079)	-31.030*** (4.060)
month _{feb}	-.039 (.053)	-.037 (.054)	.244 (2.725)
month _{mar}	-.031 (.058)	-.084 (.058)	7.350* (2.950)
month _{apr}	.026 (.059)	.007 (.059)	3.926 (3.011)
month _{may}	.039 (.059)	.057 (.059)	-.130 (3.007)
month _{jun}	-.027 (.060)	.025 (.060)	-3.865 (3.051)
month _{jul}	.043 (.063)	.112 (.063)	-7.414* (3.210)
month _{aug}	-.014 (.063)	.054 (.063)	-7.001* (3.202)
month _{sep}	.104 (.063)	.151* (.063)	-2.622 (3.221)
month _{oct}	.066 (.063)	.114 (.062)	-3.039 (3.181)
month _{nov}	.127* (.063)	.219*** (.063)	-8.701** (3.202)
month _{dec}	.134* (.059)	.243*** (.059)	-11.275*** (3.003)
day _{tue}	-.027* (.011)	-.030* (.012)	.007 (.579)
day _{wed}	.022 (.014)	.020 (.015)	-.041 (.738)
day _{thu}	.011 (.016)	-.004 (.016)	1.588* (.801)
day _{fri}	-.039* (.016)	-.070*** (.016)	3.365*** (.802)
day _{sat}	-.512*** (.014)	-.504*** (.015)	-.554 (.737)
day _{sun}	-.111*** (.011)	-.127*** (.012)	3.029*** (.579)
ρ (autocorrelation)	.729	.717	.726
σ_u (between-group std.-dev.)	1.512	1.357	20.99
σ_e (within-group std.-dev.)	.190	.194	9.715
R^2 (within-group explained variance)	.561	.517	.121
R^2 (overall explained variance)	.584	.549	.227
Observations	2188	2188	2188
F Statistic (df = 22; 2164)	125.5***	105.5***	13.53***

*** $p < .001$, ** $p < .01$, * $p < .05$, standard errors in parentheses

which stated that threshold-based free shipping would lead to more sales compared to fixed-fee shipping.

Second, we find that threshold-based free shipping significantly increases the daily number of orders (model 3.1b in Table 3.3) for the group of orders where shipping fees decreased. The increase amounts to .361 in the logged order count ($p < .001$) or, by exponentiating, 43.58% in the non-logged order count. We do not find a significant effect within the group of orders where shipping fees increased. As before, this is an indication for a negative effect of increased shipping fees on the number of orders, which is parried by threshold-based free shipping. In sum, there is partial evidence in support of H2, which stated that threshold-based free shipping would lead to more orders compared to fixed-fee shipping.

Third, we find no evidence for a significant effect of threshold-based free shipping on the daily average order value (model 3.1c in Table 3.3), though both groups of orders have a consistent negative effect direction. Consequently, we cannot confirm H3, which stated that threshold-based free shipping would lead to smaller orders compared to fixed-fee shipping.

Regarding control variables in the three models 3.1a-3.1c, we find significant effects of various year, month and day control variables. First, sales decrease in 2018 and 2019. This effect seems to be driven by a substantial and steady decrease in order value over time instead of order count over time, as year has no significant effect on the logged order count. Second, we find evidence for monthly variation in all models: Sales and the number of orders show an increase especially in the last two months of the year, while the value of an order is lowest during this period. Third, regarding days of the week, sales and the number of orders are lowest in the weekend and highest in the middle of the week, and the order value is highest on Fridays. All models show high temporal autocorrelation (above .7). Finally, the explained variance for each model is highly significant, though the model fit is considerably higher for sales and order count than for order value.

3.5.2 Influence of Shipping Fee on Product Returns

Return Probability Across all Products

Regarding the product-purchase level dataset, we find that threshold-based free shipping significantly increases the return probability (model 3.2 in Table 3.4). This holds both for products where shipping fees increased and for products where shipping fees decreased, although the strength of the effect varies (.014, $p = .034$, for increasing shipping fees, and .091, $p < .001$, for decreasing shipping fees). Transforming the log odds into probabilities, we get that expected product returns increase from 30.07% to 30.36% with threshold-based free shipping and increased product shipping fees, and

Table 3.4: Influence of threshold-based free shipping and type of purchase (filler versus regular) on return probability

Dependent variable:	Returned (3.2)	Returned (3.3)
Constant _{shipping fee up}	−.844*** (.006)	−.857*** (.006)
Constant _{shipping fee down}	.092*** (.002)	.087*** (.002)
threshold-based free shipping _{shipping fee up}	.014* (.006)	
filler purchase × threshold-based free shipping _{shipping fee up}		−.131*** (.011)
regular purchase × threshold-based free shipping _{shipping fee up}		.018** (.006)
threshold-based free shipping _{shipping fee down}	.091*** (.002)	
filler purchase × threshold-based free shipping _{shipping fee down}		−.363*** (.003)
regular purchase × threshold-based free shipping _{shipping fee down}		.098*** (.002)
price	.003*** (.000)	.003*** (.000)
discounted	−.040*** (.001)	−.039*** (.001)
basket size	.052*** (.000)	.051*** (.000)
last in basket	−.322*** (.001)	−.294*** (.001)
age	−.004*** (.000)	−.004*** (.000)
gender _{male}	−.253*** (.001)	−.253*** (.001)
years of customer patronage	.011*** (.000)	.011*** (.000)
year ₂₀₁₇	.028*** (.001)	.029*** (.001)
year ₂₀₁₈	.054*** (.001)	.055*** (.001)
year ₂₀₁₉	.096*** (.001)	.098*** (.001)
month _{feb}	.029*** (.001)	.029*** (.001)
...		
month _{dec}	.028*** (.001)	.027*** (.001)
day _{tue}	.002* (.001)	.002* (.001)
...		
day _{sun}	−.005*** (.001)	−.005*** (.001)
cat _{accessoires}	−1.145*** (.001)	−1.141*** (.001)
...		
cat _{toys}	−2.811*** (.004)	−2.799*** (.004)
Observations	83 704 086	83 704 086
Log-likelihood	−49 282 562.71	−49 254 263.10
BIC	98 565 982.84	98 509 420.10

*** $p < .001$, ** $p < .01$, * $p < .05$, standard errors in parentheses

from 52.30% to 54.56% with threshold-based free shipping and decreased product shipping fees. This is empirical support in favor of H₄, which stated that threshold-based free shipping would lead to more returns compared to fixed-fee shipping.

Return Probability of Filler and Regular Purchases under the Threshold-Based Policy

Next, we estimate the effect on threshold-based free shipping on the returns of filler purchases and regular purchases (model 3.3 in Table 3.4). Here, we find a significant effect of threshold-based free-shipping policy for filler and regular purchases, but in opposite directions. Filler purchases are returned significantly less with threshold-based free shipping whereas regular purchases are returned more. Again, the strength of the effect depends on whether the product belongs to the group with increasing or decreasing shipping fees. For filler purchases, returns decrease by $-.131$ (from 29.80% to 27.13%, $p < .001$) in the former case and by $-.363$ (from 52.17% to 43.14%, $p < .001$) in the latter case. For regular purchases, returns increase by $.018$ (from 29.80% to 30.17%, $p = .005$) and by $.098$ (from 52.17% to 54.61%, $p < .001$), respectively. These findings are supportive empirical evidence for H_{5a} (against H_{5b}), which stated that, with threshold-based free shipping, filler purchases would be returned less (more) than regular purchases.

A priori Return Probability of Filler and Regular Purchases

Finally, we extend the previous model (3.3) by also distinguishing between products that fall under the definition of regular and filler purchases within a fixed-fee shipping policy (model 3.4). By doing so, we can uncover differences in return probability that might be an outcome of the definition of the purchase type alone. As such, it helps us to understand to what extent regular and filler purchases have a different return probability, regardless of the shipping policy, and to what extent this difference is attenuated/mitigated by the introduction of the new policy.

The results confirm and extend the findings of the previous model: purchases classified as regular purchases have a higher inherent return probability than purchases classified as filler purchases – with both shipping policies. The introduction of threshold-based free shipping then further widens the gap between both types of purchases, i.e., it further increases the return probability of regular purchases and decreases the return probability of filler purchases. Concretely, for regular purchases, we observe an increase in returns from 29.82% to 30.17% ($-.856$ to $-.839$ in log odds) and from 52.25% to 54.59% ($.090$ to $.184$ in log odds) for the product group with increased and decreased shipping fees, and for filler purchases, we find a decrease in returns from 28.19% to 27.11% ($-.935$ to $-.989$ in log odds) and from 45.02% to 43.09%

Table 3.5: Influence of shipping policy (threshold-based free shipping versus fixed-fee shipping) and type of purchase (filler versus regular) on return probability in a full factorial design

Dependent variable:	Returned (3.4)
filler purchase $\times$ fixed-fee shipping _{shipping fee up}	-.935*** (.047)
filler purchase $\times$ threshold-based free shipping _{shipping fee up}	-.989*** (.009)
regular purchase $\times$ fixed-fee shipping _{shipping fee up}	-.856*** (.006)
regular purchase $\times$ threshold-based free shipping _{shipping fee up}	-.839*** (.003)
filler purchase $\times$ fixed-fee shipping _{shipping fee down}	-.200*** (.008)
filler purchase $\times$ threshold-based free shipping _{shipping fee down}	-.278*** (.003)
regular purchase $\times$ fixed-fee shipping _{shipping fee down}	.090*** (.002)
regular purchase $\times$ threshold-based free shipping _{shipping fee down}	.184*** (.002)
price	.003*** (.000)
discounted	-.039*** (.001)
basket size	.051*** (.000)
last in basket	-.293*** (.001)
age	-.004*** (.000)
gender _{male}	-.253*** (.001)
years of customer patronage	.011*** (.000)
year ₂₀₁₇	.029*** (.001)
year ₂₀₁₈	.055*** (.001)
year ₂₀₁₉	.098*** (.001)
month _{feb}	.029*** (.001)
...	
month _{dec}	.027*** (.001)
day _{tue}	.002* (.001)
...	
day _{sun}	-.005*** (.001)
cat _{accessoires}	-1.141*** (.001)
...	
cat _{toys}	-2.799*** (.004)
Observations	83 704 086
Log-likelihood	-49 253 549.63
BIC	98 508 029.64

*** $p < .001$, ** $p < .01$, * $p < .05$, standard errors in parentheses

3 Influence of Fixed-Fee/Threshold-Based Free Shipping on Orders and Returns

(−.200 to −.278 in log odds) for both product groups (Table 3.5).

In order to test the significance of the difference in return probability due to purchase type (i.e., filler and regular purchase) and shipping policy, we conduct post-hoc Wald tests (Table 3.6).

Table 3.6: Wald test results for inequality of parameter estimates

Parameter	Significance of difference (p-value Wald test)						
	vs.	(a)	(b)	(c)	(d)	(a)-(c)	(b)-(d)
filler purchase × fixed-fee shipping _{shipping fee up}	(a)		.257	.090			
filler purchase × threshold-based free shipping _{shipping fee up}	(b)	.257			< .001		
regular purchase × fixed-fee shipping _{shipping fee up}	(c)	.090			.009		
regular purchase × threshold-based free shipping _{shipping fee up}	(d)		< .001	.009			
	(a)-(c)						.139
	(b)-(d)					.139	
	vs.	(e)	(f)	(g)	(h)	(e)-(g)	(f)-(h)
filler purchase × fixed-fee shipping _{shipping fee down}	(e)		< .001	< .001			
filler purchase × threshold-based free shipping _{shipping fee down}	(f)	< .001			< .001		
regular purchase × fixed-fee shipping _{shipping fee down}	(g)	< .001			< .001		
regular purchase × threshold-based free shipping _{shipping fee down}	(h)		< .001	< .001			
	(e)-(g)						< .001
	(f)-(h)					< .001	

We find that influence of purchase type is significant in all cases, i.e., that regular purchases are always returned more than filler purchases regardless of changes in shipping policy and shipping fee ($p < .001$ to $p = .090$, conditions (a) vs. (c) and (b) vs. (d) as well as (e) vs. (g) and (f) vs. (h) in Table 3.6). The influence of shipping policy is significant, i.e., increasing returns for regular purchases and decreasing returns for filler purchases ($p < 0.001$, conditions (c) vs. (d) as well as (e) vs. (f) and (g) vs. (h) in Table 3.6) – except for such filler purchases, where shipping fees increased ($p = .257$, condition (a) vs. (b) in Table 3.6). Finally, by combining these effects, we find that threshold-based free shipping leads to a significantly wider gap in return probability when shipping fees decrease and to a non-significantly wider gap when shipping fees increase ($p < .001$ and $p = .139$, conditions (a) - (c) vs. (b) - (d) in Table 3.6). Thus, filler purchases have a significantly lower return rate than regular purchases, and this difference increases under the threshold-based free shipping policy.

Product Return Model Diagnostics

We find each new version of the return model performing slightly better than the previous one, as indicated by a decreasing BIC. With regards to control variables, we

find very similar effects across all three models for product returns. Price, a larger shopping basket size, and years of customer patronage have a significant, positive influence on return probability, whereas a discount, being the last product in the shopping basket, an additional year of age of the customer, and male gender have a significant, negative influence on return probability. Product returns significantly increase each year and vary per month and product category. Table 6.1 and Table 6.2 in the appendix (section 6.2) show the estimates of model (3.2), (3.3), and (3.4) including all control variables (i.e., encompassing all product category and month dummy variables).

3.5.3 Post-Estimation Profiling of Filler Purchases

Figure 3.4: Price distribution of filler and regular purchases

In the previous section, we showed empirically that filler purchases have a distinct return pattern – with a lower return rate than that of regular purchases – and that this pattern is reinforced under the threshold-based free shipping policy. To further the understanding of filler purchases and why they are returned less than regular purchases, we proceed with a post-hoc analysis and contrast both types of purchases in terms of price and product categories. First, regarding the price distribution, we observe that filler purchases have a median price of €17.95 (mean: €25.63), which is substantially lower than the median price of regular purchases of €29.95 (mean: €43.25) and just below the free shipping threshold. The histogram (Figure 3.4) shows that filler and regular purchases have a roughly similar price distribution with the important difference that filler purchases are much more likely to lie in the €0-€20 price range. Second, regarding product categories, we find that filler purchases belong more often to product categories such as toys, health, and beauty, and less often to ladies' fashion, men's fashion, and shoes, compared to regular purchases (Figure 3.5).

Figure 3.5: Category distribution of filler and regular purchases

In conclusion, both the price and product category distributions show that filler purchases are distinct from regular purchases. Moreover, their different characteristics fit well with our reasoning for why their return rate would be lower: categories in which filler purchases are overrepresented often contain products that are recurring purchases (e.g., the categories health, beauty, and baby), or are purchased as gifts (toys).

3.5.4 Simulation of the Impact of Shipping Policy on Profitability

In our results, we find that the overall effect of the shipping policy change is composed of both beneficial (i.e., higher sales) as well as detrimental (i.e., higher returns) effects from the retailer's perspective. In order to have an overall assessment of profit implications, taking into account both beneficial and detrimental effects, we proceed to simulate the effect of the shipping policy change on the one-year sales-based cumulative profit. We vary both the profit margin and return processing cost, thus providing insights on the circumstances under which a threshold-based free shipping fee policy is relatively more/less profitable compared to a fixed-fee shipping policy. We calculate the overall change in one-year cumulative profits between the two shipping policies as the sum of three components: 1. change in daily net sales (i.e., sales excluding returns) times the gross margin, 2. change in daily received shipping fees, and 3. change in daily cost of return handling² :

1. We input the assumed margin directly (e.g., margin = 45%) and then calcu-

² As our models are estimated at the daily level, we first determine the change in profit at the daily level, and subsequently multiply with 365 (days) to obtain the total change in cumulative profit for the whole year.

late the difference of net sales with threshold-based free shipping and net sales with fixed-fee shipping. To obtain net sales, we predict sales from model (3.1a), calculate the probability of not returning – using predicted product returns from model (3.2), as we use overall return probability – and then multiply both values.

2. For the change in daily received shipping fees, we calculate the daily received shipping fees for both fixed-fee shipping and threshold-based free shipping and calculate their difference. We obtain daily received shipping fees by multiplying the shipping fee per order under the respective shipping policy with the predicted number of orders from model (3.1c).
3. For the change in daily cost of return handling, we calculate daily return cost with fixed-fee shipping and subtract it from the daily return cost with threshold-based free shipping. The daily return cost is the return processing cost (i.e., the cost of an individual return) times the number of daily returns. We input the return processing cost directly (e.g., return processing cost = €6) and calculate the number of daily returns by multiplying the predicted number of daily orders from model (3.1c) with the average number of products per order and with the predicted return probability from model (3.2).

We present detailed calculations for each step in the appendix (subsection 6.2.2). Figure 3.6 shows the resulting difference in one-year cumulative profits based on a range of plausible return processing costs and gross margins. We assume that the return processing cost is at least as high as the current shipping fee (about €3) of our retailer and vary the profit margin around the reported gross margin for online retailing (of 42.5%, Damodaran, 2021).

We find that, across all return processing cost scenarios, retailers with average and above-average gross margins always profit from introducing threshold-based free shipping, even when return processing costs are high. In other words, in all included scenarios, these retailers win when switching to this policy, and additional profits of doing so are substantial. When the profit margin is considerably below average, return processing cost should become a consideration. However, even for retailers with below-average gross margins, threshold-based free shipping is almost always more profitable. Only in case of very high return processing costs (i.e., €12) and low margins (i.e., 37.5%), fixed-fee shipping is the more profitable option.

Figure 3.6: Profitability of shipping policy change

3.6 Discussion

3.6.1 Conclusions

In this paper, we compared the consequences of two wide-spread shipping policies of online retailers –threshold-based free shipping and fixed-fee shipping – on both purchases and returns. Regarding purchases, we decompose overall sales into order value and order count. Regarding returns, we investigate whether so-called filler purchases – purchases that make the order value surpass the required threshold for threshold-based free shipping – explain contrasting return quotas for fixed-fee and threshold-based free shipping. Insights provided in this paper are based on the analysis of a unique dataset from a major European online retailer that contains information on 26.21 million orders of 83.79 million items from 3.81 million customers in a three years period (from July, 2016 to June, 2019), and covers a broad range of product categories. Since the retailer introduced threshold-based free shipping together with order-dependent shipping fee changes, we separately consider two groups of purchases: those where shipping fees have increased, and those where shipping fees have decreased.

The results are partly in line with what we predicted (Table 3.7). In partial support of our theoretical argument, threshold-based free shipping is likely to increase sales and the number of orders. We reasoned that fixed-fee shipping always results in

Table 3.7: Summary of the findings

Hypothesis	Findings
H1 Threshold-based free shipping leads to higher sales compared to fixed-fee shipping	Partially supported
H2 Threshold-based free shipping leads to more orders compared to fixed-fee shipping	Partially supported
H3 Threshold-based free shipping leads to a lower average order value compared to fixed-fee shipping	Not supported
H4 Threshold-based free shipping leads to more returns compared to fixed-fee shipping	Supported
H5a Threshold-based free shipping leads to less returns of filler purchases compared to regular purchases	Supported
H5b Threshold-based free shipping leads to more returns of filler purchases compared to regular purchases	Not supported

shipping fees whereas threshold-based free shipping policy is, as the name implies, potentially free. Consequently, customers have to pay less shipping fees on average with threshold-based free shipping. Since customers are very sensitive to price, in general, and shipping cost, in particular, theory predicts that customers will order less with the more expensive policy, i.e., fixed-fee shipping (Bijmolt et al., 2005; Smith & Brynjolfsson, 2001). The empirical results show that there are more orders and, consequently, higher sales with threshold-based free shipping than with fixed-fee shipping for one group of orders. In particular, for the group of orders with decreasing shipping fees, we find 45.21% higher sales and 43.58% more orders. For the remaining orders – with increasing shipping fees, we find no significant effect of threshold-based free shipping versus free shipping. The combination of a large positive effect in the first group and the absence of a negative effect in the second group (with increasing shipping fees) is likely evidence of an overall positive effect of threshold-based free shipping on the number of orders and sales.

We find no evidence for our theoretical argument that threshold-based free shipping would lead to orders with lower value. We theorized that fixed-fee shipping would be an incentive for customers to delay purchases in order to distribute them among fewer and larger orders and, thereby, reduce the total of due shipping fees. Threshold-based free shipping, on the other hand, would only incentivize customers to delay purchases up to the free shipping threshold, as a further delay does not reduce total shipping costs. Therefore, threshold-based free shipping is a more constrained incentive for combining smaller into larger orders than fixed-fee shipping and thus retains smaller orders. However, our results indicate that order size (in terms of mon-

etary value) is not influenced by shipping policy.

In addition, we find that the shipping policy influences return behavior. We expected that threshold-based free shipping would increase returns for two reasons. The first reason is irrational customer behavior with regards to sunk cost (Domeier et al., 2018). Shipping fees are non-refundable and therefore a sunk cost when returning. However, customers tend to not admit that cost is sunk, because it appears wasteful (Arkes & Blumer, 1985), and so they choose a course of action that avoids writing it off – the so-called “Concorde fallacy” (Carter et al., 2007). When keeping products instead of returning them, customers do not have to write off shipping fees. Since fixed-fee shipping more often necessitates writing off shipping fees than threshold-based free shipping, the former incentivizes keeping instead of returning more than the latter. The second reason for expecting threshold-based free shipping to lead to more returns than fixed-fee shipping is economic customer behavior with regards to the cost of re-ordering. When customers think about returning a purchase and ordering a slightly different product, the benefit of returning and re-ordering has to outweigh its cost (Anderson et al., 2009; Petersen & Kumar, 2015). This cost is often lower with threshold-based free shipping, where shipping is potentially free, than with fixed-fee shipping, where shipping is always paid, and therefore the cost-benefit-ratio with the former more often permits returning than with the latter. Our empirical results show that shipping policy influences returns. Threshold-based free shipping slightly increases returns by 0.29% and 2.26%, depending on how shipping fees changed. Therefore, in line with our theoretical argument, we find that shipping policy influences returns, although effect sizes are small to moderate.

Besides, we find that the small, positive effect of threshold-based free shipping on returning is both reversed and amplified for returning of filler purchases. Here, threshold-based free shipping leads to less product returns. In particular, for filler purchases, returns decrease between 1.08% and 1.93% due to the introduction of threshold-based free shipping. A post-estimation analysis of filler purchases shows that categories in which such purchases are overrepresented comprise many recurring purchases (e.g., health, beauty and baby product categories) and gifts (toys product category). We hence find support for our hypothesis that threshold-based free shipping would incentivize customers to order additional products, which they would have ordered anyway but at a later point in time. Those products have been shown to be likely regularly purchased products with a consequently lower return rate (Petersen & Kumar, 2009). We find no support for our opposite hypothesis that threshold-based free shipping would lead to more returns of filler purchases due to customers intentionally planning to order and return in order to abuse the shipping policy and obtain free shipping. While customers thus show intentional and planned behavior by ordering distinct, less returned products as filler purchases, customers show no signs of malevolent behavior by ordering and returning to circumvent shipping fees.

3.6.2 Managerial Implications

Our paper compares the impact of two straightforward and widely used shipping fee policies, fixed-fee shipping and threshold-based free shipping, on both purchases and returns, and our findings have important managerial implications.

First, we find that threshold-based free shipping has the advantage of substantially higher sales and more orders, while fixed-fee shipping leads to a lower return rate. Thus, our findings indicate that threshold-based free shipping is in most circumstances advantageous for the retailer. In a simulation, we find that a retailer with an average gross margin for online retailing (of 42.5%, Damodaran, 2021) makes higher profits with threshold-based free shipping than with fixed-fee shipping with return processing costs per product of up to €12. For retailers with lower gross margins, return processing costs are of greater concern and very low margins coupled with very high return processing costs can make fixed-fee shipping more profitable: in our simulation, only a retailer with a gross margin of 37.5% or less and return processing costs of €12 or more, would be better off with fixed-fee shipping than with threshold-based free shipping.

Second, we do not find evidence for strategic abuse of threshold-based free shipping policies. Instead, threshold-based free shipping leads customers to order products, which they anticipate to need anyway, as filler purchases and return those purchases less than their other purchases. Since filler purchases are thus returned less than regular purchases, it would be beneficial for retailers to actively promote such purchases, e.g., by having a wish list function or suggesting recurrently ordered products at the order checkout page.

3.6.3 Limitations and Future Research

Our study is based on the purchase and return data of several million customers over the course of three years at a generalist online retailer. Even though the retailer is large and carries an assortment that covers most products that a generally ordered online, it is still a single retailer in one country. Therefore, repeating the analysis for different retailers in different markets could give further support to our findings. In addition, having only data from one retailer prevents us from observing customer switching behavior. Therefore, we cannot say whether the increase in sales from our retailer is paralleled by decreased sales from its competitors. Finally, we do not find evidence for customers circumventing threshold-based free shipping using filler purchases, on average. A laboratory or field experiment might help to shed light on possible boundary conditions for such strategic behavior.

4

Effects of Price Reductions on Customer Return Behavior

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. On the one hand, price reductions lead to more returns for customers that have returned due to a price reduction before. On the other hand, 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.

4.1 Introduction

Online retailers dynamically adapt prices for promotional or strategic reasons in order to respond to demand changes, inventory level, and competitors' prices (Elmaghraby & Keskinocak, 2003; Fisher et al., 2018; Grewal, 2011; Grewal et al., 2010). While numerous studies have shown that a decrease in price fosters sales (Bijmolt et al., 2005; Gupta, 1988) and changes price and brand perception (e.g., Blattberg et al., 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 (Directive 2011/83/EU, 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 & 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.

4.2 Conceptual 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 et al., 2005; Cooke et al., 2001) and might in both cases influence returning.

4.2.1 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 et al., 2016). As a consequence, on an aggregate level, price reductions generally increase short-term sales (Bijmolt et al., 2005; Gupta, 1988).

Price reductions, however, likely also have an impact on return behavior. Generally, product returns arrive out of a state of cognitive dissonance. After having obtained the purchased product, customers evaluate it with regards to prior expectations (Kotler et al., 2019). If the purchase falls short of expectations, customers will experience a dissonant state of regret (Powers & Jack, 2015). 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 & Pieters, 2007, p. 3). Since regret leads to “strong wishes to undo the current situation” (Zeelenberg & Pieters, 2007, p. 3), customers might want to undo the purchase by returning the product. Based on this mechanism, price reductions could both lead to more or less returning.

One the one hand, research shows that customers use price to form product quality expectations (e.g., Grewal, 1995; Voss et al., 1998). If the product price is lower due to

a price reduction, customers might therefore have lower expectations, which makes regretting and returning the purchase less likely. In addition, Petersen and Kumar (2009) have empirically shown that products on sale are returned less than regularly priced products. In sum, a reduced price might lower expectations and therefore lead to less product returns.

On the other hand, price reductions can increase impulse buying (Kacen et al., 2012; Xu & Huang, 2014). The crucial difference between regular and impulse purchases is the amount of information that is sought before the purchase decision (Lee & Kacen, 2008). With less information available to the customer, chances are higher that the purchase does not fulfil customers expectations. As a result, impulse purchases are more likely to be regretted than regular purchases (Grigsby et al., 2021). In sum, a reduced price might also lead to more impulse purchases and therefore to more product returns.

Therefore, 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.

4.2.2 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 et al. (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: as mentioned above, after purchase, customers evaluate their purchase by comparing perceived performance with prior expectations (Kotler et al., 2019). When expectations are not fully met, customers can try to confirm the value of their purchase by outside sources and thereby reduce dissonance (V.-W. Mitchell & 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 et al., 2001; Simonson, 1992; Tsiros & Hardesty, 2010; Zeelenberg & Pieters, 2007). 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 et al., 2015) and customers might want to undo their current purchase. 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.

4.2.3 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 & Kumar, 2009, 2015; Shah et al., 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 regretted and returned (Grigsby et al., 2021; Kacen et al., 2012; Xu & Huang, 2014). The tendency of impulse buying has been linked to a consumer's personality traits by numerous studies (e.g., Sharma et al., 2010; Wells et al., 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 et al., 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 & Morich, 2011, p. 493). According to Shah et al. (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.

4.2.4 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 et al., 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 & 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 moderat-

ing 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 & 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 & 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 & Pavlou, 2014; Petersen & 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 & Krishnamurthi, 2012). But, purchase of seasonal products is prone to regret (Petersen & 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 & Kumar, 2009), and cost savings might generally be less important as gifts are seen as symbols for relationship value (Larsen & 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 & 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 et al., 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.

4.3 Data

4.3.1 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.

4.3.2 Variables

Figure 4.1: 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

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 price¹, 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

¹ We follow the terminology by van Heerde et al. (2000) in denoting a price without a reduction as the regular price.

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 4.1).

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 4.1).

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 4.1: 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)	Freq.: 32.79%
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	Freq.: 9.55%
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%

Table 4.1: Dependent and independent variables used in the analysis (continued)

Variable	Definition	Data summary
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: 205.27 SD: 263.76
Basket size	Total number of products ordered together with the product	Mean: 5.77 SD: 6.30
Purchase price	Product purchase price	Mean: 50.28 SD: 99.17
Delivery fee	Cost of delivering the order	Mean: .08 SD: .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: 42 years SD: 11.61
Gendermale	Whether customer's gender is male	female: 80.08% male: 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%

Table 4.1: Dependent and independent variables used in the analysis (continued)

Variable	Definition	Data summary
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: 58.85 SD: 93.93
Number of articles	Number of articles in the category (that were purchased at least once during the observation period)	Mean: 1351.25 SD: 2653.55
Number of brands	Number of brands in the category (that were purchased at least once during the observation period)	Mean: 38.66 SD: 35.16

4.4 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 & Mayhew, 1997; Minnema et al., 2016; Petersen & 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.

4.4.1 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 $t = [1, \dots, 31]$ 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.

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

$$S(t) = P(T > t)$$

$$T : \text{random variable denoting the time before return} \quad (4.1)$$

(possibly infinite)

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

$$\lambda(t) = -\frac{S'(t)}{S(t)} = \lim_{dt \rightarrow 0} \frac{1}{dt} \frac{P(t \leq T < t + dt)}{S(t)}, \quad (4.2)$$

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

$$S'(t) = \frac{d}{dt} S(t). \quad (4.3)$$

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 et al., 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 & Jones, 2004; Hosmer et al., 2008). Therefore, we resort to a spline-based model, as originally suggested by Royston and Parmar (2002), which allows for non-proportional hazards.

The model by Royston and Parmar (2002) incorporates survival as a spline function for the baseline hazard plus a sum of splines for 1, ..., D time-dependent effects (thus allowing for non-proportional hazards) plus all time-independent effect of covariates x multiplied by the coefficients β :

$$\ln(-\ln(S(t; x))) = s(\ln(t)|\gamma) + \sum_{j=1}^D s(\ln(t)|\delta_j)x_j + x\beta \quad (4.4)$$

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

$$s(\ln(t); p) = \sum_{k=1}^K B_k(\ln(t)) p_k \quad (4.5)$$

and $B_k(\ln(t))$ is a natural spline basis with K degrees of freedom (Clements, 2019; Royston & 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.

4.4.2 Analysis Models

Using the model from equation (4.4) as a basis, we formulate three models to estimate the effect of price reductions on product returns². 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 (4.4), our first model (i) then is:

$$\ln(-\ln(S(t; x_{t,i}))) = s(\ln(t)|\gamma) + s(\ln(t)|\delta_1)x_{1,i} + s(\ln(t)|\delta_2)x_{2,t,i} + x_{t,i}\beta. \quad (4.6)$$

with:

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

γ vector of baseline spline coefficients,

β vector of intercept and coefficients for all included variables,

$x_{t,i} = (1, x_{1,i}, x_{2,t,i}, x_{3,i}, \dots, x_{22,i})$ 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

δ_1, δ_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

² Owing to the formulation of survival models, we formally model the chance of a product return *not* happening, i.e., the chance of keeping a product.

with price reductions. That is, we extend $x_{t,i}$ 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).

4.4.3 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 together³. 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 en-

³ Available working memory limits the data size to a maximum of about 1000 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.

tire 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 & Lambert, 2011).

4.4.4 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 4.6) 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 cross-category survival difference. For that, we regress an intercept on survival difference due to a change in each variable v_i :

$$\widehat{\Delta S}_{v_i} = \vec{1}\alpha_{v_i} + \varepsilon_{v_i} \quad (4.7)$$

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 $(0, 0, \dots, 0)$, i.e., a vector of zeros for all days $t = [0, 31]$, to $x^* = (1, 1, \dots, 1)$. 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:

$$\widehat{\Delta S}_{d_i} = \vec{1}\alpha_{d_i} + z_{d_i}\beta_{d_i} + \varepsilon_{d_i} \quad (4.8)$$

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.

4.5 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.

4.5.1 Immediate Effects of Price Reductions on Returning

Table 4.2: 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 ¹
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***
Gender _{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***

¹ *** $p < .001$, ** $p < .01$, * $p < .05$

Table 4.2 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 (.3 percent points, $p < .001$), providing no empirical evidence for H1a, H1b, or H2.

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 prob-

ability 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.

4.5.2 Influence of Prior Return Behavior

Table 4.3: 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 ¹
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 ²	-.034	.002	-21.557	< .001***
Prior returner with: price reduction post-purchase ³	-.042	.002	-21.362	< .001***
Prior returner	-.059	.004	-15.908	< .001***
Gender _{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***

¹ *** $p < .001$, ** $p < .01$, * $p < .05$

² Purchase is during a price reduction and the customer has returned in such a case before

³ Purchase is followed by a price reduction and the customer has returned in such a case before

Table 4.3 presents insights on the extent to which customers' prior return behav-

ior 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 direction of the overall effect. Therefore, we find support for H3 and partial support for H1b.

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 direction of 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.

4.5.3 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 4.4 show that heavy returners drive the effect of prior returners while light returners are more similar to customers who have not returned before.

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 (+.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.

Table 4.4: 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 ¹
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 ²	.013	.001	15.816	< .001***
Light returner with: price reduction post-purchase ³	.003	.001	4.180	< .001***
Heavy returner with: purchase during price reduction ⁴	-.023	.001	-19.016	< .001***
Heavy returner with: price reduction post-purchase ⁵	-.036	.002	-20.619	< .001***
Light returner ⁶	-.007	.001	-6.658	< .001***
Heavy returner ⁷	-.076	.004	-17.214	< .001***
Gender _{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***

¹ *** $p < .001$, ** $p < .01$, * $p < .05$

² Purchase is during a price reduction and the customer has returned in such a case before (1-2 times)

³ Purchase is followed by a price reduction and the customer has returned in such a case before (1-2 times)

⁴ Purchase is during a price reduction and the customer has returned in such a case before (3+ times)

⁵ Purchase is followed by a price reduction and the customer has returned in such a case before (3+ times)

⁶ Customer has returned before (1-2 times)

⁷ Customer has returned before (3+ times)

Light returners of any prior purchase have a slightly lower chance of keeping the purchase (−.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.

4.5.4 Category-level Heterogeneity

Figure 4.2: 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

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 4.2). The

Table 4.5: 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***

*** $p < .001$, ** $p < .01$, * $p < .05$

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 4.2, 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 4.2, third row), light returners have more mixed and less significant effects (Figure 4.2, second row).

Next, we relate the cross-category differences to the product characteristics, using equation (4.8). Table 4.5 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 ($R^2 = .397$ and $.392$), least for light returners ($R^2 = .315$ and $.081$), and price reductions in general in between ($R^2 = .168$ 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.

4.6 Discussion

4.6.1 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 4.6 presents an overview of our findings.

Table 4.6: Summary of the findings

Findings:		
H1a	– Customers are more likely to return a product that is purchased during a price reduction.	not supported
H1b	– Customers are less likely to return a product that is purchased during a price reduction.	partially supported
H2	– Customers are more likely to return a product with a post-purchase price reduction.	not supported
H3	– 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
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.	supported
Empirical findings on product category differences:		
<ul style="list-style-type: none"> – 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 & Hardesty, 2010; Zeelenberg & 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 et al., 2010), which are returned more (Kacen et al., 2012; Xu & 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 et al., 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.

4.6.2 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.

4.6.3 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 & Verhoef, 2016), a future study could investigate whether such cross-firm effect exists.

5

General Discussion

Contemporary retailing business is marked by two important trends: the trend towards omni-channel retailing, where multiple channels coexist and intertwine, and the trend of increasing importance of the online channel (Verhoef & Bijmolt, 2019; Verhoef et al., 2015). Both trends create a range of challenges for retailers. First, multiple channels need to intertwine as seamlessly as possible (Bijmolt et al., 2019). In addition, one channel might influence the business of other channels. The first study (chapter 2) of this dissertation therefore empirically investigated the influence of an offline channel on purchases and returns in the online channel. Second, the growth of the online channel exacerbates problems of the online retailing business. One of the largest issues threatening the profitability of customer relationships (Asdecker, 2015) and, by extension, of the whole retailer, are product returns (Minnema et al., 2018). The second and third study (chapter 3 and chapter 4) of this dissertation therefore empirically investigated whether shipping policy and price reductions, respectively, can influence and reduce product returns. This chapter summarizes and discusses the findings of the previous chapters and, subsequently, points out avenues for future research.

5.1 Main Findings and Implications per Chapter

This section revisits the overarching research questions from chapter 1. First the questions are restated. Then, the associated empirical chapter is summarized and discussed. Finally, the chapter's findings are used to answer the research question.

5.1.1 Influence of Stores on Online Orders and Returns

RQ1 What are the effects of physical stores on online channel customer behavior in terms of product purchases and returns?

Many retailers nowadays are multi-channel retailers that offer both an online channel as well as traditional brick-and-mortar stores. However, both channels do not exist independently from each other. Instead, the offline channel might exert an influence on customer behavior in the online channel. In particular, the presence of brick-and-mortar stores in proximity to the customer could influence the number of online product purchases and returns. Regarding online purchases, offline stores might either detract online customers due to channel substitution and web-rooming or attract online customers due to cross-channel promotion (Mitra & Fay, 2010; Neslin & Shankar, 2009). Regarding online returns, customers might use offline stores to show-room or purchase risky products, thereby decreasing returns. On the other hand, customers might also return more since more stores mean more parcel drop-off points and easier returning. To investigate whether and to which extent offline

stores influence online purchases and returns, the study in chapter 2 uses a novel spatial regression model and online purchase and store location data from a large Dutch retailer.

Results show that the number of offline stores in proximity to a customer does influence customer behavior in the online channel. First, offline stores reduce the number of online product returns. Their effect on product returns is driven by products that have a higher perceived risk for the customer. Offline stores decrease returns of products with higher perceived risk (i.e., products with multiple sizes, a higher price or no discount) but do not influence returns of products with lower perceived risk (i.e., products with a single size, a lower price or a discount). Depending on the type of product, more offline stores can lead to up to 13.91% to 16.26% less returns, as indicated by a post-estimation simulation study. Second, offline stores do not influence online purchases. The number of offline stores in proximity neither influences the number of purchased shopping baskets per customer nor the number of purchased products per shopping basket, regardless of the perceived risk level of the product.

With regards to the first research question, the study in chapter 2 therefore indicates an overall beneficial effect of physical stores on online channel customer behavior. Whereas in terms of product purchases, offline stores do not influence online channel customer behavior, in terms of product returns, offline stores have a beneficial effect.

5.1.2 Influence of the Shipping Policy on Online Orders and Returns

RQ2 What are the consequences of threshold-based free shipping in comparison to fixed-fee shipping on orders, returns, and profitability?

In online retailing, when customers have placed an order, the order has to be prepared for shipment and, subsequently, shipped to the address of the customer. This process is costly and question is, who will pay for it. Retailers often charge part of the cost to the customer as so-called shipping fees. In their shipping policy, retailers can decide to impose fees on all or some orders, based on e.g., order value or product category. However, since shipping fees increase the cost of an order and customers are sensitive to costs (Bijmolt et al., 2005; Smith & Brynjolfsson, 2001), a side-effect of shipping fees might be changed purchase or return behavior from customers. Therefore, retailers need to be aware of the consequences on purchases and return based on how they apply shipping fees.

The study in chapter 3 compares two wide-spread shipping policies: fixed-fee shipping, where a fixed fee is applied to an order irrespective of its size, and threshold-based free shipping, where a fee is applied to all orders below a certain order value threshold. Theory predicts that fixed-fee shipping, in comparison to threshold-based

free shipping, might incentivize customers to distribute their product purchases among fewer larger orders in order to minimize shipping cost. In addition, threshold-based free shipping might incentivize customers to purchase and afterwards return so-called filler purchases, i.e., purchases that make the order value surpass the free-shipping threshold, and thereby allow to circumvent paying shipping fees. To confirm the theoretical argument, the study empirically compares both shipping policies in terms of daily-level sales, order count, and order value as well as product-level product returns. The analysis is based on a large dataset from a major European retailer, containing more than 26 million orders in a broad range of categories by more than 3.8 million customers in a three years period.

Results show that the shipping policy has an influence on customers' order and return behavior. Regarding order behavior, there is evidence that threshold-based free shipping increases the number of orders and leads to higher overall sales than fixed-fee shipping, in line with the theoretical argument. On the other hand, threshold-based free shipping does not significantly change the monetary value of an order. Regarding return behavior, threshold-based free shipping leads to slightly more returns than fixed-fee shipping. This is not due to filler purchases, however, which are returned less often than regular (i.e., non-filler) purchases. Finally, the study concludes with a profitability simulation, which shows that the positive effects of threshold-based free shipping on customers' order behavior likely outweigh its negative effects on customers' return behavior under most conditions and, therefore, that threshold-based free shipping leads to a higher profitability than fixed-fee shipping in almost all investigated scenarios.

In sum, the answer to the overarching research question of chapter 3 is that threshold-based free shipping is, under most circumstances, more profitable than fixed-fee shipping. The higher profitability stems from an increase in the number of orders and, by that, an increase in sales and is in spite of a slightly higher return probability.

5.1.3 Influence of Price Reductions on Online Returns

RQ3 Are products more (or less) likely to be returned (a) when they are purchased during a price reduction or (b) when there is a price reduction after purchase?

Online retailers vary the prices of their products with the aim to increase purchases. Price reduction might not only influence customer purchase behavior but also customer return behavior. The effect could theoretically be positive or negative and might extend to both returns of purchases that are bought during a price reduction as well as returns of purchases that were bought before a price reduction and are still eligible to be returned (Grewal, 1995; Kacen et al., 2012; Petersen & Kumar, 2009; Tsiros & Hardesty, 2010). In addition, the effect might depend on prior customer

behavior, i.e., how a customer usually responds to price reductions, and on the product category of the purchase (Shah et al., 2014; Sharma et al., 2010). Overall, price reductions might sometimes be more or less suitable for retailers, when considering their effect on product returns. Managerially, an encompassing understanding of the effects of price reductions is important in order to know when (not) to employ them.

The study in chapter 4 investigates empirically whether online purchases are more or less likely to be returned due to a price reduction (a) at the time of purchase or (b) after the purchase and during the return period. The regression analysis using a survival regression model (Royston & Parmar, 2002) is based on a vast and unique dataset of a European online retailer. In particular, more than 83 million purchases and more than 37 million returns in more than 300 categories used as the basis for the analysis.

Results show that price reductions influence returning. However, the effect of price reductions on returning is strongly dependent on whether or not a customer has returned products with at/post- purchase price reductions before. In particular, for customers that have not returned a purchase with a price reduction previously, a price reduction will lead to slightly less returns. For customers, that have returned a purchase with a price reduction previously, a price reduction will lead to slightly more returns, i.e., the effect is reversed. Zooming into the latter effect, it turns out that the increase is mainly driven by customers who have returned more than two purchases with a price reduction before. Importantly, all aforementioned effects are present for both price reductions (a) at the time of purchase and (b) after the purchase, i.e., during the return period, and consistently hold for almost all product categories. For search goods, utilitarian, and gift categories, the effect size tends to be smaller, however.

The research question of chapter 4 asked whether products are more or less likely to be returned when there is a price reduction during or after their purchase. The results show that price reductions can lead to both more and less returns. The effect strength and directionality is dependent on customers recurrent reaction to such promotions. Customers who usually return a product when there is a price reduction, are more likely to do so again than customers who have not engaged in such behavior before. Besides, whether a price reduction takes place during or after purchase has little influence on its effect direction or strength on product returns.

5.2 Overall Conclusion and Future Research Opportunities

Omni-channel retailing in general, and online retailing in particular, bring about a range of challenges. Numerous studies have investigated such challenges for omni-

channel and online retailers (Bijmolt et al., 2019; Minnema et al., 2018). This dissertation addresses three areas where prior research was limited. In particular, the study in chapter 2 shows that physical stores are a means to reduce returns in the online channel, especially for products with higher perceived risk. Furthermore, the reduction in returns is not accompanied by a reduction in online purchases. Consequently, online retailers might benefit from considering having physical stores in addition to an online channel. The study in chapter 3 shows that the retailers' shipping policy influences purchases and returns. Threshold-based free shipping leads to higher sales and more orders whereas fixed-fee shipping leads to less returns. When comparing both policies in terms of profitability, threshold-based free shipping is likely advantageous for most retailers. Finally, the study in chapter 4 shows that price reductions of online retailers influence product returns. In particular, price reduction increase returns of customers, who have a habit of returning due to price reductions and decrease returns of customers, who do not have the habit. Consequently, online retailers might benefit from selectively promoting price reduction to customers who are not prone to returning reduced products. In sum, all three chapters find parameters that significantly influence returning with practical relevance for retailers.

For future research, the steadily rising importance of omni-channel retailing and the development of new technologies will provide novel and interesting research topics. In addition to that, the continuing digitization of business and society increases data availability of therefore provides a growing foundation for empirical research (Verhoef & Bijmolt, 2019). At the same time, legal limits with regards to privacy and subjective privacy concerns by customers should to be part of the research.

One avenue for future research might comprise the investigation of how much integration between channels is beneficial for omni-channel retailers. For example, many retailers provide online accounts and loyalty cards. By coupling both, retailers could recommend products online based on offline shopping behavior and vice versa. Additionally, many online customers abandon their shopping carts (Rochanapon et al., 2021) and in-store personnel might fruitfully recommend products from such abandoned shopping carts. Future research could investigate to which extent integrative measures between channels profit retailers and when customers feel positively assisted or negatively impacted in their privacy.

Furthermore, the online channel is becoming more important in the quick commerce and rapid delivery sector. Spurred by the covid-19 pandemic, customers increasingly order groceries, prepared meals and items from local shops online (Butler, 2021). As part of that, many privately-owned local restaurants and stores that previously did not offer their items online, have commenced to do so. Future research could investigate whether adding an online channel is beneficial for such small businesses, as brand perception, margins and the customer base might be positively or negatively affected in the long-term.

In the future, technology that allows people to experience an augmented reality (AR) is expected to become more wide-spread. Research could investigate to what extent it is beneficial for channels to use AR and, as one possibility, converge into a combined physical and virtual experience. Already, some retailers provide customers the ability to use their phone or tablet to view their products as virtual objects in the real world (Rese et al., 2017). For example, IKEA offers an app that allows consumers to view virtual furniture in their physical home and thereby evaluate product fit (White, 2021). When AR applications become easier and more convenient for customers, online shopping at home would be able to transition to a more store-like experience, e.g., by allowing customers to view virtual replicas of physical products or to be provided assistance by store personnel at home. In addition, AR technologies could make shopping at a store more like online shopping, e.g., by enriching the store experience with features from online shopping such as wish list functionality and customer reviews. Future research might investigate which retailers and products would benefit most from such technology and which kinds of applications customers would prefer.

Finally, some formerly physical products can be replaced entirely by digital products. Books and newspapers as well as films, music, and games are increasingly bought in digital form (European Commission & ICF International, 2015; Warman, 2020). Legal requirements with regards to returns of downloaded products are often less strict and, consequently, the leniency for returns of such products varies considerably from retailer to retailer (e.g., Hoffman, 2019) and is generally stricter than for physical goods. Little is known with regards to the effect of lenient return policies on returns of digital goods as prior research almost exclusively focused on returns of physical goods (Minnema et al., 2018). One exception is the study by Schulz et al. (2019), who find that returns of paid online news article are lower when they have been promoted by newsletters and when they have more likes. Future research might investigate the effects of return policy leniency with regards to digital goods and other retailer actions, such as targeted promotions, on purchases and returns of digital products.

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6

Appendix

6.1 Appendix for chapter 2

6.1.1 Approximation of the Spatial Durbin Error Term

The computation of the error term u relies on the inverse of a function of the fixed weighting matrix and the variable spatial autocorrelation parameter ρ :

$$u = f(\rho)\varepsilon = (I - \rho W)^{-1}\varepsilon, \quad (6.1)$$

An approximation using the Neumann series allows us to avoid computing the inverse, which would be computationally expensive, and still gives decent results. The Neumann series for a matrix M is defined as

$$(I - M)^{-1} = \sum_{k=0}^{\infty} M^k \quad (6.2)$$

with I being the identity matrix. If we substitute $M = \rho W$, we get

$$(I - \rho W)^{-1} = \sum_{k=0}^{\infty} \rho^k W^k = f(\rho). \quad (6.3)$$

In practice, we use the Neumann series of sixth order, so that we have

$$f(\rho) \approx I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \rho^4 W^4 + \rho^5 W^5 \quad (6.4)$$

which we use to calculate u in (6.1).

Using this method to approximate u , we found a correlation of more than 0.99 when comparing exact and approximately calculated u for different values of ρ for our concrete weight matrix W . The benefit is that we can pre-compute the powers of the large matrix W , as they do not depend on the parameter ρ , before the estimation. During the estimation, we just need to multiply each pre-computed W^k by a scalar, and the overall sum by a vector. The resulting gain in efficiency is high: Calculating the exact value in R takes about half a minute whereas the approximation – when relying on precomputed powers of W – takes around one second. LeSage and Pace (2009) propose a conceptually related method.

6.1.2 Model Convergence

In general, there needs to be convergence within and between the so-called chains, to be able to use and interpret the model estimates. A chain is a stochastic process, whose equilibrium distribution is the (posterior density) estimate of the model parameters. There should hence be no continuous movement of a chain in one direction,

indicating that the equilibrium distribution has not been reached. There needs to be convergence between chains, i.e., all chains need to converge to a similar value, irrespective of their (random) starting value (Brooks et al., 2011). The so-called potential scale reduction factor (PSRF or $\hat{R}$) is usually used to check convergence. It compares “the variance of the simulations from each chain [...], average[s] these within-chain variances, and compare[s] this to the variances of all the chains mixed together” (Brooks et al., 2011, p. 170). The square root of the latter (variance of all chains taken together) divided by the former is $\hat{R}$. The estimates of the burn-in phase are not included in the calculation. A value of one indicates ideal convergence, while a $\hat{R}$ value of less than 1.1 is usually considered as acceptable (Brooks et al., 2011). All relevant parameters of all aforementioned models are estimated with an $\hat{R}$, which lies in the acceptable range of < 1.1 .

6.1.3 Simulation

To verify the estimation process, we simulated data according to the model specification. Our simulated dataset is approximately of the size of the real dataset at each hierarchical level ($J = 4000$ regions; $M = 10\,000$ customers; $N = 15\,000$ orders). The assignment of lower levels to higher levels is made so that it mirrors that real dataset. Practically, we base the assignment on an appropriate gamma distribution and then transform the result to assure that all lower level observations are assigned to a higher level. Concerning the spatial weight matrix, we assign up to 18 neighbors to each region, with the distance based on the inverse of the absolute difference in row/column numbers in the matrix. On the order and client level, we use five independent variables, on the regional level two and on the cross-regional level three. For each, we draw random data from $U(0, 1)$. Estimation shows that for the both the zero-truncated as well as the regular Poisson case, true parameters are recovered generally well: 19 parameters out of 19 lie in the 95% credibility interval (i.e. 100%) and 17 out of 19 in the 90% credibility interval (i.e. 89%) for the zero-truncated Poisson case. 17 out of 19 lie in the 95% credibility interval and in the 90% credibility interval for the regular Poisson case. The cross-regional parameters are always recovered in the 90% (and thus 95%) credibility interval.

6.2 Appendix for chapter 3

6.2.1 Extended Tables

Table 6.1: Influence of threshold-based free shipping and type of purchase (filler versus regular) on return probability

Dependent variable:	Returned (3.2)	Returned (3.3)
Constant _{shipping fee up}	−.844*** (.006)	−.857*** (.006)
Constant _{shipping fee down}	.092*** (.002)	.087*** (.002)
threshold-based free shipping _{shipping fee up}	.014* (.006)	
filler purchase × threshold-based f.s. _{shipping fee up}		−.131*** (.011)
regular purchase × threshold-based f.s. _{shipping fee up}		.018** (.006)
threshold-based free shipping _{shipping fee down}	.091*** (.002)	
filler purchase × threshold-based f.s. _{shipping fee down}		−.363*** (.003)
regular purchase × threshold-based f.s. _{shipping fee down}		.098*** (.002)
price	.003*** (.000)	.003*** (.000)
discounted	−.040*** (.001)	−.039*** (.001)
basket size	.052*** (.000)	.051*** (.000)
last in basket	−.322*** (.001)	−.294*** (.001)
age	−.004*** (.000)	−.004*** (.000)
gender _{male}	−.253*** (.001)	−.253*** (.001)
years of customer patronage	.011*** (.000)	.011*** (.000)
year ₂₀₁₇	.028*** (.001)	.029*** (.001)
year ₂₀₁₈	.054*** (.001)	.055*** (.001)
year ₂₀₁₉	.096*** (.001)	.098*** (.001)
month _{feb}	.029*** (.001)	.029*** (.001)
month _{mar}	.029*** (.001)	.028*** (.001)
month _{apr}	−.015*** (.001)	−.016*** (.001)
month _{may}	−.029*** (.001)	−.030*** (.001)
month _{jun}	−.024*** (.001)	−.025*** (.001)
month _{jul}	−.069*** (.001)	−.068*** (.001)
month _{aug}	−.040*** (.001)	−.040*** (.001)
month _{sep}	.067*** (.001)	.066*** (.001)
month _{oct}	.079*** (.001)	.078*** (.001)
month _{nov}	.055*** (.001)	.053*** (.001)
month _{dec}	.028*** (.001)	.027*** (.001)
day _{tue}	.002* (.001)	.002* (.001)
day _{wed}	.004*** (.001)	.004*** (.001)
day _{thu}	.001 (.001)	.001 (.001)
day _{fri}	−.008*** (.001)	−.008*** (.001)
day _{sat}	.000 (.001)	−.000 (.001)
day _{sun}	−.005*** (.001)	−.005*** (.001)
cat _{accessoires}	−1.145*** (.001)	−1.141*** (.001)
cat _{baby}	−1.384*** (.002)	−1.379*** (.002)
cat _{beachwear}	.345*** (.001)	.348*** (.001)
cat _{beauty}	−2.105*** (.004)	−2.099*** (.004)
cat _{electronics}	−2.204*** (.002)	−2.201*** (.002)
cat _{garden}	−2.236*** (.004)	−2.234*** (.004)
cat _{health}	−2.427*** (.010)	−2.419*** (.010)
cat _{home}	−2.026*** (.001)	−2.021*** (.001)

Table 6.1: Influence of threshold-based free shipping and type of purchase (filler versus regular) on return probability (continued)

Dependent variable:	Returned (3.2)	Returned (3.3)
cat _{kids_fashion}	−.961*** (.001)	−.959*** (.001)
cat _{lingerie}	−.787*** (.001)	−.784*** (.001)
cat _{mens_fashion}	−.617*** (.001)	−.617*** (.001)
cat _{nightwear}	−.926*** (.002)	−.920*** (.002)
cat _{other}	−9.126*** (.447)	−9.145*** (.447)
cat _{shoes}	−.216*** (.001)	−.219*** (.001)
cat _{sports}	−.500*** (.001)	−.500*** (.001)
cat _{toys}	−2.811*** (.004)	−2.799*** (.004)
Observations	83 704 086	83 704 086
Log-likelihood	−49 282 562.71	−49 254 263.10
BIC	98 565 982.84	98 509 420.10

*** $p < .001$, ** $p < .01$, * $p < .05$, standard errors in parentheses

Table 6.2: Influence of shipping policy (threshold-based free shipping versus fixed-fee shipping) and type of purchase (filler versus regular) on return probability in a full factorial design

Dependent variable:	Returned (3.4)
filler purchase × fixed-fee shipping _{shipping fee up}	−.935*** (.047)
filler purchase × threshold-based free shipping _{shipping fee up}	−.989*** (.009)
regular purchase × fixed-fee shipping _{shipping fee up}	−.856*** (.006)
regular purchase × threshold-based free shipping _{shipping fee up}	−.839*** (.003)
filler purchase × fixed-fee shipping _{shipping fee down}	−.200*** (.008)
filler purchase × threshold-based free shipping _{shipping fee down}	−.278*** (.003)
regular purchase × fixed-fee shipping _{shipping fee down}	.090*** (.002)
regular purchase × threshold-based free shipping _{shipping fee down}	.184*** (.002)
price	.003*** (.000)
discounted	−.039*** (.001)
basket size	.051*** (.000)
last in basket	−.293*** (.001)
age	−.004*** (.000)
gender _{male}	−.253*** (.001)
years of customer patronage	.011*** (.000)
year ₂₀₁₇	.029*** (.001)
year ₂₀₁₈	.055*** (.001)
year ₂₀₁₉	.098*** (.001)
month _{feb}	.029*** (.001)
month _{mar}	.028*** (.001)

Table 6.2: Influence of shipping policy (threshold-based free shipping versus fixed-fee shipping) and type of purchase (filler versus regular) on return probability in a full factorial design (continued)

Dependent variable:	Returned (3.4)
month _{apr}	-.016*** (.001)
month _{may}	-.030*** (.001)
month _{jun}	-.025*** (.001)
month _{jul}	-.068*** (.001)
month _{aug}	-.040*** (.001)
month _{sep}	.066*** (.001)
month _{oct}	.077*** (.001)
month _{nov}	.053*** (.001)
month _{dec}	.027*** (.001)
day _{tue}	.002* (.001)
day _{wed}	.004*** (.001)
day _{thu}	.001 (.001)
day _{fri}	-.008*** (.001)
day _{sat}	-.000 (.001)
day _{sun}	-.005*** (.001)
cat _{accessoires}	-1.141*** (.001)
cat _{baby}	-1.379*** (.002)
cat _{beachwear}	.348*** (.001)
cat _{beauty}	-2.099*** (.004)
cat _{electronics}	-2.201*** (.002)
cat _{garden}	-2.235*** (.004)
cat _{health}	-2.419*** (.010)
cat _{home}	-2.021*** (.001)
cat _{kids_fashion}	-.959*** (.001)
cat _{lingerie}	-.784*** (.001)
cat _{mens_fashion}	-.617*** (.001)
cat _{nightwear}	-.920*** (.002)
cat _{other}	-9.146*** (.447)
cat _{shoes}	-.219*** (.001)
cat _{sports}	-.500*** (.001)
cat _{toys}	-2.799*** (.004)
Observations	83 704 086
Log-likelihood	-49 253 549.63
BIC	98 508 029.64

*** $p < .001$, ** $p < .01$, * $p < .05$, standard errors in parentheses

6.2.2 Profitability Simulation

We calculate the overall change in one-year cumulative profits between the two shipping policies as the sum of three components: (1) change in daily sales (excluding returns) $\times$ the gross margin, (2) change in daily received shipping fees, and (3) change in daily cost of return handling:

$$\Delta \text{profit/year} = (\Delta \text{netsales/day} \times \text{margin} + \Delta \text{shippingfees/day} - \Delta \text{returncost/day}) \times 365 \quad (6.5)$$

1. The first part of the overall calculation consists of multiplying the difference in daily net sales (i.e., post-returns) with an assumed margin. We input the assumed margin directly (e.g., margin = 45%) and then calculate the difference of net sales with threshold-based free shipping (abbreviated as tbfs) and net sales with fixed-fee shipping (abbreviated as ffs). Since we estimated baseline sales and the effect of tbfs separately for categories with rising and falling shipping fees, we need to calculate 2×2 net sales values:

$$\begin{aligned} \Delta \text{netsales/day} = & (\text{netsales/day}_{\text{tbfs,shippingfetdown}} \\ & + \text{netsales/day}_{\text{tbfs,shippingfeeup}}) \\ & - (\text{netsales/day}_{\text{ffs,shippingfetdown}} \\ & + \text{netsales/day}_{\text{ffs,shippingfeeup}}) \end{aligned} \quad (6.6)$$

Since sales estimations from model (3.1) includes returned items, we need to calculate net sales first. We do so by multiplying predicted sales from model (3.1) with the probability of not returning – using predicted returns from model (3.2). This needs to be done for all four netsales values from the last equation:

$$\begin{aligned} \text{netsales/day}_{\text{ffs,shippingfetdown}} = & \text{sales/day}_{\text{ffs,shippingfetdown}} \\ & \times (1 - \text{prob_returns}_{\text{ffs,shippingfetdown}}) \end{aligned} \quad (6.7)$$

$$\begin{aligned} \text{netsales/day}_{\text{tbfs,shippingfetdown}} = & \text{sales/day}_{\text{tbfs,shippingfetdown}} \\ & \times (1 - \text{prob_returns}_{\text{tbfs,shippingfetdown}}) \end{aligned} \quad (6.8)$$

$$\begin{aligned} \text{netsales/day}_{\text{ffs,shippingfeeup}} = & \text{sales/day}_{\text{ffs,shippingfeeup}} \\ & \times (1 - \text{prob_returns}_{\text{ffs,shippingfeeup}}) \end{aligned} \quad (6.9)$$

$$\begin{aligned} \text{netsales/day}_{\text{tbfs,shippingfeeup}} = & \text{sales/day}_{\text{tbfs,shippingfeeup}} \\ & \times (1 - \text{prob_returns}_{\text{tbfs,shippingfeeup}}) \end{aligned} \quad (6.10)$$

Now, we proceed to predict sales and returns. First, we predict sales using the estimates of model (3.1) using (a) the baseline sales + (b) effect of tbfs, if applicable + (c) effect of control variables. In particular, we only include (b) when calculating sales with threshold-based free shipping and we include (c) as: $1/4$ of each year covariate, $1/12$ of each month covariate, $1/7$ of each day covariate, and $\frac{\text{orders_in_category}_i}{\text{total_orders}}$ times each category i covariate:

$$\text{sales/day}_{\text{ffs,shippingfeedown}} = \exp(\alpha_{\text{shippingfeedown}} + \text{covariates}) \quad (6.11)$$

$$\begin{aligned} \text{sales/day}_{\text{tbfs,shippingfeedown}} = \exp(\alpha_{\text{shippingfeedown}} \\ + \beta_{\text{tbfs,shippingfeedown}} + \text{covariates}) \end{aligned} \quad (6.12)$$

$$\text{sales/day}_{\text{ffs,shippingfeeup}} = \exp(\alpha_{\text{shippingfeeup}} + \text{covariates}) \quad (6.13)$$

$$\begin{aligned} \text{sales/day}_{\text{tbfs,shippingfeeup}} = \exp(\alpha_{\text{shippingfeeup}} \\ + \beta_{\text{tbfs,shippingfeeup}} + \text{covariates}) \end{aligned} \quad (6.14)$$

$$\begin{aligned} \text{with: covariates} = \frac{1}{4} \sum_{i=1}^3 \beta_{\text{year}_i} + \frac{1}{12} \sum_{i=1}^{11} \beta_{\text{month}_i} \\ + \frac{1}{7} \sum_{i=1}^6 \beta_{\text{day}_i} + \sum_{i=1}^{16} \frac{\text{orders_in_category}_i}{\text{total_orders}} \beta_{\text{category}_i} \end{aligned} \quad (6.15)$$

Second, we predict returns. We calculate the four prob_returns using the estimates of the logit model (2.2) and, besides, proceed similarly as for the prediction of sales:

$$\text{prob_returns}_{\text{ffs,shippingfeedown}} = \text{logit}^{-1}(\alpha_{\text{shippingfeedown}} + \text{covariates}) \quad (6.16)$$

$$\begin{aligned} \text{prob_returns}_{\text{tbfs,shippingfeedown}} = \text{logit}^{-1}(\alpha_{\text{shippingfeedown}} \\ + \beta_{\text{tbfs,shippingfeedown}} + \text{covariates}) \end{aligned} \quad (6.17)$$

$$\text{prob_returns}_{\text{ffs,shippingfeeup}} = \text{logit}^{-1}(\alpha_{\text{shippingfeeup}} + \text{covariates}) \quad (6.18)$$

$$\begin{aligned} \text{prob_returns}_{\text{tbfs,shippingfeeup}} = \text{logit}^{-1}(\alpha_{\text{shippingfeeup}} \\ + \beta_{\text{tbfs,shippingfeeup}} + \text{covariates}) \end{aligned} \quad (6.19)$$

with covariates as defined above but using the estimates of the return model.

2. The second part of the overall calculation consists of the change in daily received shipping fees. Here, we calculate the daily received shipping fees for

both the ffs and tbfs policies and take the difference of both. Again, we need to do this two times – for categories where shipping fees decreased and for categories where shipping fees increased – and add the results:

$$\begin{aligned} \Delta \text{shippingfees/day} = & (\text{shippingfees/day}_{\text{tbfs,shippingfetdown}} \\ & + \text{shippingfees/day}_{\text{tbfs,shippingfeeup}}) \\ & - (\text{shippingfees/day}_{\text{ffs,shippingfetdown}} \\ & + \text{shippingfees/day}_{\text{ffs,shippingfeeup}}) \end{aligned} \quad (6.20)$$

Each part of the equation is calculated by: (a) the applicable shipping fee $\times$ (b) predicted number of orders:

$$\begin{aligned} \text{shippingfees/day}_{\text{ffs,shippingfetdown}} = & \text{fee}_{\text{ffs,shippingfetdown}} \\ & \times \text{count_orders}_{\text{ffs,shippingfetdown}} \end{aligned} \quad (6.21)$$

$$\begin{aligned} \text{shippingfees/day}_{\text{tbfs,shippingfetdown}} = & \text{fee}_{\text{tbfs,shippingfetdown}} \\ & \times \text{count_orders}_{\text{tbfs,shippingfetdown}} \end{aligned} \quad (6.22)$$

$$\begin{aligned} \text{shippingfees/day}_{\text{ffs,shippingfeeup}} = & \text{fee}_{\text{ffs,shippingfeeup}} \\ & \times \text{count_orders}_{\text{ffs,shippingfeeup}} \end{aligned} \quad (6.23)$$

$$\begin{aligned} \text{shippingfees/day}_{\text{tbfs,shippingfeeup}} = & \text{fee}_{\text{tbfs,shippingfeeup}} \\ & \times \text{count_orders}_{\text{tbfs,shippingfeeup}} \end{aligned} \quad (6.24)$$

For (a), we calculate the average observed shipping fee for the respective orders, i.e., the average shipping fee for (1) orders with threshold-based free shipping in categories where shipping fees decreased, (2) orders with threshold-based free shipping in categories where shipping fees increased, etc.:

$$\text{fee}_{\text{ffs,shippingfetdown}} = \text{€}6.297 \quad (6.25)$$

$$\text{fee}_{\text{tbfs,shippingfetdown}} = \text{€}0.098 \quad (6.26)$$

$$\text{fee}_{\text{ffs,shippingfeeup}} = \text{€}7.766 \quad (6.27)$$

$$\text{fee}_{\text{tbfs,shippingfeeup}} = \text{€}2.47 \quad (6.28)$$

For (b), we get the number of daily orders using the estimates of model (3.1),

similar to how we did the first predictions:

$$\text{count_orders/day}_{\text{ffs,shippingfeedown}} = \exp(\alpha_{\text{shippingfeedown}} + \text{covariates}) \quad (6.29)$$

$$\begin{aligned} \text{count_orders/day}_{\text{tbfs,shippingfeedown}} &= \exp(\alpha_{\text{shippingfeedown}} \\ &\quad + \beta_{\text{tbfs,shippingfeedown}} + \text{covariates}) \end{aligned} \quad (6.30)$$

$$\text{count_orders/day}_{\text{ffs,shippingfeeup}} = \exp(\alpha_{\text{shippingfeeup}} + \text{covariates}) \quad (6.31)$$

$$\begin{aligned} \text{count_orders/day}_{\text{tbfs,shippingfeeup}} &= \exp(\alpha_{\text{shippingfeeup}} \\ &\quad + \beta_{\text{tbfs,shippingfeeup}} + \text{covariates}) \end{aligned} \quad (6.32)$$

with covariates as defined above but using the estimates of the count order model.

3. The third part of the overall calculation is the change in daily cost of return handling. We calculate this part by subtracting the daily return cost with fixed-fee shipping from the daily return cost with threshold-based free shipping:

$$\Delta \text{returncost/day}_{\text{sum}} = \text{returncost/day}_{\text{sum,tbfs}} - \text{returncost/day}_{\text{sum,ffs}} \quad (6.33)$$

where each part is (a) cost-per-return $\times$ (b) number-of-daily-returns with ffs or tbfs. We input (a) as fixed numbers (e.g., $\text{returncost}_{\text{per_return}} = \text{€}6$) but do not have (b). We can calculate (b) by: the estimate of the number of daily orders $\times$ number of products per orders $\times$ the return probability of a product. Again, we need to do this separately for ffs and tbfs policies and for rising and falling

shipping fees. We thus get:

$$\begin{aligned}
 \text{returncost/day}_{\text{sum,ffs}} &= \text{returncost}_{\text{per_return}} \\
 &\quad \times (\text{prob_returns}_{\text{ffs,shippingfeedown}} \\
 &\quad \times \text{ordersize}_{\text{ffs,shippingfeedown}} \\
 &\quad \times \text{count_orders/day}_{\text{ffs,shippingfeedown}} \quad (6.34) \\
 &\quad + \text{prob_returns}_{\text{ffs,shippingfeeup}} \\
 &\quad \times \text{ordersize}_{\text{ffs,shippingfeeup}} \\
 &\quad \times \text{count_orders/day}_{\text{ffs,shippingfeeup}})
 \end{aligned}$$

$$\begin{aligned}
 \text{returncost/day}_{\text{sum,tbfs}} &= \text{returncost}_{\text{per_return}} \\
 &\quad \times (\text{prob_returns}_{\text{tbfs,shippingfeedown}} \\
 &\quad \times \text{ordersize}_{\text{tbfs,shippingfeedown}} \\
 &\quad \times \text{count_orders/day}_{\text{tbfs,shippingfeedown}} \quad (6.35) \\
 &\quad + \text{prob_returns}_{\text{tbfs,shippingfeeup}} \\
 &\quad \times \text{ordersize}_{\text{tbfs,shippingfeeup}} \\
 &\quad \times \text{count_orders/day}_{\text{tbfs,shippingfeeup}})
 \end{aligned}$$

For the number of products per order, we calculate the average value for the respective orders with the following result:

$$\text{ordersize}_{\text{ffs,shippingfeedown}} = 3.619 \quad (6.36)$$

$$\text{ordersize}_{\text{tbfs,shippingfeedown}} = 3.351 \quad (6.37)$$

$$\text{ordersize}_{\text{ffs,shippingfeeup}} = 1.388 \quad (6.38)$$

$$\text{ordersize}_{\text{tbfs,shippingfeeup}} = 1.593 \quad (6.39)$$

For the return probability, we use the values predicted in the first step.

7

Nederlandstalige samenvatting

De detailhandel is grondig veranderd. E-commerce is een belangrijk onderdeel van het retailvak geworden. Tussen 2010 en 2020 is het aantal consumenten dat recentelijk online heeft besteld verdubbeld, van ongeveer een derde naar ongeveer twee derde (Eurostat, 2021b, 2021c). Vooral modeartikelen zoals kleding en schoenen worden in alle leeftijdsgroepen vaak online besteld (Eurostat, 2021a). In het kader van deze ontwikkeling hebben veel voormalige fysieke retailers hun activiteiten uitgebreid naar het internet (Deloitte, 2018; Zaczekiewicz, 2018), en zijn er nieuwe online-first retailers ontstaan (Statista, 2019). Hoewel de onlinedetailhandel aan belang blijft winnen, heeft deze de offlinedetailhandel niet verdrongen. In plaats daarvan verwachten klanten dat retailers meerdere kanalen, d.w.z. online én offline, beschikbaar stellen (Bijmolt e.a., 2019). Veel retailers hebben dan ook een zogenaamd multi- of omni-channel bedrijfsmodel omarmd (CB Insights, 2018; Thompson, 2017). Bij een multi- of omni-channel model zijn klanten niet beperkt tot één kanaal, zoals een fysieke winkel van de retailer, en kunnen zij voor de verschillende stappen van de customer journey met verschillende kanalen in aanraking komen.

De opkomst van omni-channel retailing en het toenemende belang van het online-kanaal stellen retailers voor uitdagingen. Ten eerste moeten retailers de verschillende kanalen op elkaar afstemmen. Dit betreft beslissingen over assortiment en voorraad, distributie en levering, en ook het retourproces (Bijmolt e.a., 2019). Daarnaast kan het bestaan van meerdere kanalen leiden tot interacties tussen kanalen – waarbij het ene kanaal de klanten, verkopen, retourzendingen en, tenslotte, rentabiliteit van een ander kanaal kan beïnvloeden. Ten tweede brengt het onlinekanaal zijn eigen uitdagingen met zich mee, die in belang toenemen naarmate de onlinedetailhandel verder groeit (Verhoef & Bijmolt, 2019). Een van de grootste problemen in de onlinedetailhandel is de hoge hoeveelheid retourzendingen van producten. Tot 45% van de online modeaankopen in de VS wordt geretourneerd, volgens de Leeuw e.a. (2016). Hoge retourpercentages zijn problematisch voor retailers, omdat ze de klantrelatie onrendabel kunnen maken en daardoor de winstgevendheid in zijn geheel kunnen schaden (Asdecker, 2015; Minnema e.a., 2018; Shah e.a., 2012). Bovendien is een hoog retourpercentage schadelijk voor het milieu: ten eerste leidt het heen en weer sturen van producten tussen klanten en retailers tot meer vrachtverkeer en dus tot meer uitstoot van broeikasgassen, en ten tweede leiden niet meer in de verkoop gebrachte retourzendingen tot extra afval (Edwards & McKinnon, 2009).

Dit proefschrift onderzoekt drie praktisch relevante onderwerpen voor retailers in de context van retourzendingen in omni-channel en online-retailing, waaraan in eerder onderzoek nog maar weinig aandacht is besteed. In de volgende paragrafen worden de onderwerpen, die empirisch onderzocht zijn in hoofdstuk 2, hoofdstuk 3, en hoofdstuk 4 van dit proefschrift, kort voorgesteld, en worden de belangrijkste bevindingen samengevat.

7.1 Invloed van fysieke winkels op online bestellingen en retourzendingen

Voor retailers die overwegen om een multi-channel of omni-channel model te omarmen, is het belangrijk om de voor- en nadelen van het gebruik van meerdere kanalen te kennen. Met name het aanhouden van een offline kanaal, d.w.z. van fysieke winkels, brengt hoge kosten met zich mee, zoals huur en lonen. Deze extra kosten moeten worden gecompenseerd door extra opbrengsten. Afgezien van de inkomsten die het offline kanaal zelf genereert, kunnen beide kanalen een wisselwerking hebben. Daardoor zou het offline kanaal het gedrag van de klanten in het online kanaal kunnen veranderen. Wat online aankopen betreft, kunnen fysieke winkels online klanten afleiden – door het online kanaal geheel of alleen voor de aankoop te substitueren (web-rooming), ofwel online klanten aantrekken – doordat het ene kanaal het andere promoot (cross-channel promotie, Mitra en Fay, 2010; Neslin en Shankar, 2009). Wat online retourzendingen betreft, is het mogelijk dat klanten fysieke winkels gebruiken om risicovolle producten voor de aankoop te bekijken (show-rooming) of te kopen, waardoor het aantal retourzendingen daalt. Aan de andere kant kunnen klanten ook meer retourneren, aangezien winkels als afgiftepunten voor pakketten kunnen dienen en retourneren daardoor gemakkelijker wordt. Uit eerder onderzoek blijkt dat het toevoegen van een onlinekanaal aan een offlinekanaal of, omgekeerd, het toevoegen van een offlinekanaal aan een onlinekanaal negatieve, neutrale en positieve gevolgen kan hebben (Avery e.a., 2012; Pauwels & Neslin, 2015; van Nierop e.a., 2011).

De studie in hoofdstuk 2 heeft tot doel (a) uiteenlopende resultaten uit eerder onderzoek te verklaren door risicogerelateerde productkenmerken in de analyse te integreren, en (b) een holistisch beeld te geven van de invloed van de aanwezigheid van een offline kanaal van een retailer op de resultaten van het online kanaal van diezelfde retailer - door het effect ervan op de online aankoopfrequentie, het online aankoopvolume, en het aantal online productretouren te schatten. Daartoe wordt gebruik gemaakt van een nieuw regressiemodel, waarin naast gegevens over online aankopen ook ruimtelijke winkel- en klantgegevens van een grote Nederlandse retailer zijn verwerkt.

Uit de resultaten blijkt dat het aantal fysieke winkels in de buurt van een klant wel degelijk van invloed is op het gedrag van de klant in het onlinekanaal. Ten eerste verminderen winkels het aantal online productretouren. Dit effect wordt veroorzaakt door producten met een hoger waargenomen risico voor de klant: fysieke winkels verminderen het aantal retourzendingen van producten met een hoger gepercipieerd risico (d.w.z. producten met meerdere maten, een hogere prijs of zonder korting), maar hebben geen invloed op het aantal retourzendingen van producten met een lager gepercipieerd risico (d.w.z. producten met één maat, een lagere prijs of met kor-

ting). Afhankelijk van het soort product kunnen meer offline winkels leiden tot wel 13,91% tot 16,26% minder retourzendingen, zoals blijkt uit een simulatiestudie. Ten tweede hebben offline winkels geen invloed op online aankopen. Het aantal offline winkels in de buurt beïnvloedt noch het aantal gekochte boodschappenmandjes per klant, noch het aantal gekochte producten per boodschappenmandje, ongeacht het waargenomen risiconiveau van de producten. Samenvattend wijst de studie in hoofdstuk 2 dus op een algemeen gunstig effect van fysieke winkels op het klantengedrag in het onlinekanaal. Terwijl offline winkels geen effect hebben op online productaankopen, hebben ze daarentegen wel een gunstig effect op online productretouren.

7.2 Invloed van het verzendbeleid op online bestellingen en retourzendingen

Retailers moeten een verzendbeleid kiezen dat voorschrijft of en wanneer klanten verzendkosten moeten betalen. Afhankelijk van het verzendbeleid kunnen allerlei factoren (bv. ordergrootte of productcategorie) bepalen hoeveel de klant precies moet betalen. Een belangrijke overweging voor retailers is dat de structuur van de verzendingskosten naar alle waarschijnlijkheid van invloed is op retouren en bestellingen van producten, aangezien de verzendkosten de prijs die de klanten moeten betalen rechtstreeks verhogen. Om ervoor te zorgen dat het verzendbeleid de winstgevendheid van de online retailer verhoogt, dient het het aantal bestellingen te verhogen en het aantal retouren te verlagen (Minnema e.a., 2018; Petersen & Kumar, 2015).

De studie in hoofdstuk 3 vergelijkt twee veelgebruikte verzendbeleidskeuzes in hun invloed op online aankopen en retourzendingen: (1) verzending tegen vast tarief, waarbij een vast bedrag wordt aangerekend voor een bestelling ongeacht de grootte ervan, en (2) drempelgebonden gratis verzending, waarbij een bedrag wordt aangerekend voor alle bestellingen onder een bepaalde orderwaardedrempel. Op grond van theoretische argumenten valt te verwachten dat verzending tegen vast tarief, vergeleken met drempelgebonden gratis verzending, de klanten ertoe zal aanzetten om hun productaankopen over minder maar grotere bestellingen te verdelen, om de verzendkosten zo laag mogelijk te houden. Bovendien kan een drempelgebonden gratis verzending klanten mogelijk ertoe aanzetten om zogenaamde "filleräankopen te doen, d.w.z. aankopen die de waarde van de bestelling boven de drempel voor gratis verzending laten uitkomen, en op die manier de verzendkosten te omzeilen. Om de theoretische stellingen te toetsen, worden in de studie de beide verzendmethoden empirisch vergeleken – zowel wat betreft de dagelijkse verkoop, het aantal bestellingen en de waarde van de bestellingen, alsook wat betreft het aantal teruggestuurde producten. De analyse is gebaseerd op een omvangrijke dataset van een grote Europese retailer, die meer dan 26 miljoen bestellingen in een breed scala van categorieën van

meer dan 3,8 miljoen klanten in een periode van drie jaar bevat.

De resultaten tonen aan dat het verzendbeleid wel degelijk invloed heeft op het bestel- en retourgedrag van de klanten. Wat het bestelgedrag betreft, blijkt dat drempelgebonden gratis verzending het aantal bestellingen verhoogt en tot een hogere totale verkoop leidt dan verzending tegen vast tarief. Anderzijds verandert drempelgebonden gratis verzending de monetaire waarde van een bestelling niet significant. Wat het retourgedrag betreft, leidt drempelgebonden gratis verzending tot iets meer retourzendingen dan verzending tegen vast tarief. Dit is echter niet te wijten aan "filler aankopen, die minder vaak worden geretourneerd dan gewone aankopen (d.w.z. niet-"filler aankopen). Uit een rentabiliteitssimulatie blijkt dat de positieve effecten van drempelgebonden gratis verzending op het bestelgedrag van de klanten onder de meeste omstandigheden zwaarder wegen dan de negatieve effecten op het retourgedrag van de klanten, en dat drempelgebonden gratis verzending dus in bijna alle onderzochte scenario's tot een hogere rentabiliteit leidt dan verzending tegen vast tarief. Kortom, de studie in hoofdstuk 3 toont dus aan dat drempelgebonden gratis verzending onder de meeste omstandigheden winstgevender is dan verzending tegen vast tarief, waarbij de hogere winstgevendheid het gevolg is van een toename van het aantal bestellingen en een stijging van de verkoop, ondanks een iets grotere kans op retourzendingen.

7.3 Invloed van prijsverlagingen op online retourzendingen

Veel retailers maken gebruik van dynamische prijswijzigingen. Dat wil zeggen, veel retailers passen hun online productprijzen regelmatig aan op basis van bijvoorbeeld vraagveranderingen, voorraadniveau, en prijzen van concurrenten (Elmaghraby & Keskinocak, 2003; Fisher e.a., 2018; Grewal, 2011; Grewal e.a., 2010). Wanneer de retailer de prijs van het product verlaagt, is een belangrijk positief effect meestal een stijging van de verkoop (Bijmolt e.a., 2005; Gupta, 1988). Prijsverlagingen kunnen echter ook gevolgen hebben voor het percentage retourzendingen. Belangrijk is dat de retourzendingen van twee verschillende soorten aankopen kunnen worden beïnvloed. Ten eerste zouden de retourzendingen van aankopen die tijdens een prijsverlaging worden gedaan (d.w.z. wanneer de klant een product tegen een verlaagde prijs koopt) kunnen veranderen (Petersen & Kumar, 2009). Ten tweede zouden de retourzendingen van aankopen die vóór een prijsverlaging gedaan zijn (d.w.z. wanneer de klant een hogere aankoopprijs betaald heeft dan de verlaagde prijs na de aankoop) en die nog in aanmerking komen om geretourneerd te worden, kunnen veranderen (Bandi e.a., 2018).

In de studie in hoofdstuk 4 wordt empirisch onderzocht of online aankopen meer

of minder vaak worden geretourneerd als gevolg van een prijsverlaging in de periode van de aankoop/na de aankoop maar tijdens de retourperiode. De regressieanalyse met behulp van een survival regressiemodel (Royston & Parmar, 2002) is gebaseerd op een uitgebreide en unieke dataset van een Europese retailer. Als basis voor de analyse zijn met name meer dan 83 miljoen aankopen en meer dan 37 miljoen retourzendingen in meer dan 300 categorieën gebruikt.

Uit de resultaten blijkt dat prijsverlagingen het retourneren beïnvloeden. Het effect van prijsverlagingen op het retourneren hangt echter sterk af van de vraag of een klant al eerder producten met prijsverlagingen bij/na aankoop heeft teruggestuurd. Met name voor klanten die niet eerder een aankoop met een prijsverlaging hebben geretourneerd, leidt een prijsverlaging tot iets minder retourzendingen. Voor klanten, die eerder een aankoop met een prijsverlaging hebben geretourneerd, leidt een prijsverlaging daarentegen tot iets meer retourzendingen, d.w.z. het effect is omgekeerd. Als we op dit laatste effect inzoomen, blijkt dat de toename vooral komt van klanten die meer ervaring hebben met retourneren en eerder al meer dan twee aankopen met een prijsverlaging hebben geretourneerd. Belangrijk is dat alle bovengenoemde effecten aanwezig zijn voor prijsverlagingen zowel in de periode van de aankoop als ook na de aankoop maar tijdens de retourperiode, en consequent gelden voor bijna alle productcategorieën. Voor search goods, utilitaristische en cadeau-categorieën is het effect meestal wel kleiner. Kortom, de studie in hoofdstuk 4 geeft aan dat prijsverlagingen retourzendingen kunnen bevorderen of voorkomen, waarbij de sterkte en de richting van het effect worden beïnvloed door de herhaaldelijke reactie van de klanten op dergelijke promoties.

7.4 Conclusie

Omni-channel retailing brengt een hele reeks uitdagingen met zich mee. Talrijke studies hebben dergelijke uitdagingen voor omni-channel en online retailers onderzocht (Bijmolt e.a., 2019; Minnema e.a., 2018). Dit proefschrift gaat in op drie gebieden waar eerder onderzoek nog beperkt was. De studie in hoofdstuk 2 toont aan dat fysieke winkels een middel zijn om retourzendingen in het onlinekanaal te verminderen, vooral voor producten met een hoger gepercipieerd risico. Bovendien gaat de vermindering van het aantal retourzendingen niet gepaard met een vermindering van het aantal onlineaankopen. Dientengevolge kunnen online retailers er baat bij hebben te overwegen om naast een onlinekanaal ook fysieke winkels te hebben. Uit de studie in hoofdstuk 3 blijkt dat het verzendbeleid van retailers van invloed is op aankopen en retourzendingen. Drempelgebonden gratis verzending leidt tot hogere verkopen en meer bestellingen, terwijl verzending tegen vast tarief tot minder retourzendingen leidt. Wanneer men beide strategieën vergelijkt qua winstgevendheid, is

gratis verzending op basis van drempels waarschijnlijk voordelig voor de meeste retailers. Ten slotte blijkt uit de studie in hoofdstuk 4 dat prijsverlagingen van retailers van invloed zijn op retourzendingen. Prijsverlagingen verhogen met name het aantal retourzendingen van klanten wier gewoonte het is om wegens prijsverlagingen te retourneren, en verlagen het aantal retourzendingen van klanten wier gewoonte het niet is. Bijgevolg zouden online retailers er baat bij kunnen hebben prijsverlagingen selectief te promoten bij klanten die niet geneigd zijn om afgeprijsde producten terug te sturen. Al met al wijst dit proefschrift een aantal factoren aan, die een aanzienlijke invloed hebben op het aantal terugzendingen en die van praktisch belang zijn voor retailers.

8

Deutsche Zusammenfassung

Die Einzelhandelsbranche hat sich dramatisch verändert. E-Commerce hat sich zu einem wichtigen Bestandteil des Retailgeschäfts entwickelt. Zwischen 2010 und 2020 hat sich die Zahl der Verbraucher, die vor kurzem online bestellt haben, verdoppelt, von etwa einem Drittel auf etwa zwei Drittel (Eurostat, 2021b, 2021c). Vor allem Modeartikel wie Kleidung und Schuhe werden in allen Altersgruppen häufig online bestellt (Eurostat, 2021a). Im Rahmen dieser Entwicklung haben viele ehemalige stationäre Einzelhändler ihre Aktivitäten auf das Internet ausgeweitet (Deloitte, 2018; Zaczkie-wicz, 2018), und neue, sogenannte online first Einzelhändler sind entstanden (Statista, 2019). Obwohl der Online-Einzelhandel also immer mehr an Bedeutung gewinnt, hat er den stationären Einzelhandel nicht verdrängt. Stattdessen erwarten die Kunden von den Einzelhändlern, dass sie mehrere Kanäle zur Verfügung stellen, d.h. online und offline aktiv sind (Bijmolt et al., 2019). Daher haben viele Einzelhändler ein so-geanntes Multi- oder Omni-Channel-Geschäftsmodell gewählt (CB Insights, 2018; Thompson, 2017). In einem Multi- oder Omni-Channel-Modell sind die Kunden nicht auf einen Kanal beschränkt, wie z.B. Ladengeschäfte eines Einzelhändlers, sondern können bei den verschiedenen Schritten der Customer Journey mit verschiedenen Kanälen interagieren.

Das Aufkommen des Omnichannel-Modells und die zunehmende Bedeutung des Online-Kanals stellen Einzelhändler vor Herausforderungen. Erstens müssen die Einzelhändler die verschiedenen Kanäle koordinieren. Dazu gehören Entscheidungen über Sortiment und Lagerhaltung, Vertrieb und Lieferung sowie den Rücksendeprozess. Darüber hinaus kann die Existenz mehrerer Kanäle zu Wechselwirkungen zwischen den Kanälen führen - wobei ein Kanal die Kunden, den Umsatz, die Rücksendungen und schließlich die Wirtschaftlichkeit eines anderen Kanals beeinflussen kann. Zweitens bringt der Online-Kanal eigene Herausforderungen mit sich, die mit dem weiteren Wachstum des Online-Einzelhandels immer mehr an Bedeutung gewinnen (Verhoef & Bijmolt, 2019). Eines der größten Probleme im Online-Einzelhandel ist die hohe Anzahl von Warenrückläufern. Laut (de Leeuw et al., 2016) werden bis zu 45% der Online-Modekäufe in den USA zurückgegeben. Hohe Rückgabequoten sind für Einzelhändler problematisch, da sie die Kundenbeziehung unrentabel machen können und somit die Rentabilität insgesamt beeinträchtigen (Asdecker, 2015; Minnema et al., 2018; Shah et al., 2012). Außerdem ist eine hohe Rückgabequote schädlich für die Umwelt: Erstens führt der Hin- und Rückversand von Produkten zwischen Kunden und Einzelhändlern zu mehr Verkehr und damit zu Treibhausgasemissionen, und zweitens führen nicht wiederverwertbare Rückläufer zu zusätzlichem Abfall (Edwards & McKinnon, 2009).

Die vorliegende Dissertation untersucht drei für Einzelhändler praktisch relevante Fragestellungen im Kontext von von Rücksendungen im Omnichannel- und Online-Einzelhandel, die in der bisherigen Forschung bislang weitgehend unbeachtet geblieben sind. In den folgenden Abschnitte werden die Themen, die in Kapitel 2, Kapitel 3

und Kapitel 4 dieser Dissertation empirisch untersucht wurden, kurz vorgestellt und die wichtigsten Ergebnisse zusammengefasst.

8.1 Einfluss von Ladengeschäften auf Online-Bestellungen und Retouren

Für Einzelhändler, die ein Multi-Channel- oder Omni-Channel-Modell in Betracht ziehen, ist es wichtig, die Vor- und Nachteile der Nutzung mehrerer Kanäle zu verstehen. Insbesondere die Unterhaltung eines Offline-Kanals, d.h. von physischen Ladengeschäften, ist mit hohen Kosten wie Miete und Löhnen verbunden. Diese zusätzlichen Kosten müssen durch zusätzliche Einnahmen ausgeglichen werden. Abgesehen von den Einnahmen, die durch den Offline-Kanal selbst generiert werden, können beide Kanäle sich gegenseitig beeinflussen. Dadurch kann der Offline-Kanal das Verhalten der Kunden im Online-Kanal verändern. Ladengeschäfte können Kunden vom Online-Kanal abwerben - durch Substitution des Online-Kanals als Ganzes oder nur für den Produktkauf (Web-Rooming) - oder anwerben - da ein Kanal für den anderen wirbt (Cross-Channel-Promotion, Mitra und Fay, 2010; Neslin und Shankar, 2009). Neben Online-Käufen betrifft das auch Online-Rücksendungen: es wäre möglich, dass Kunden Ladengeschäfte nutzen, um Produkte mit hohem Risiko vorab zu begutachten (Show-Rooming) oder zu kaufen, wodurch sich die Zahl der Rücksendungen im Online-Kanal verringert. Andererseits wäre es möglich, dass Kunden die Ladengeschäfte als bequemere Annahmestellen für Pakete nutzen, was Rücksendungen erleichtert und dadurch erhöht. Frühere Untersuchungen haben gezeigt, dass das Hinzufügen eines Online-Kanals zu einem Offline-Kanal oder umgekehrt das Hinzufügen eines Offline-Kanals zu einem Online-Kanal negative, neutrale und positive Auswirkungen haben kann (Avery et al., 2012; Pauwels & Neslin, 2015; van Nierop et al., 2011).

Die Studie in Kapitel 2 zielt darauf ab, (a) die unterschiedlichen Ergebnisse früherer Untersuchungen zu erklären, indem risikobezogene Produktmerkmale in die Analyse einbezogen werden, und (b) einen ganzheitlichen Blick auf den Einfluss der Verfügbarkeit eines Offline-Kanals eines Einzelhändlers auf die Ergebnisse des Online-Kanals desselben Einzelhändlers zu werfen - durch Schätzung seiner Auswirkungen auf die Frequenz und das Volumen von Käufen sowie die Anzahl der Rücksendungen im Online-Kanal. Zu diesem Zweck wird ein neues Regressionsmodell verwendet, das zusätzlich zu Daten über Online-Käufe auch räumliche Filial- und Kundenstandortdaten eines großen niederländischen Einzelhändlers einbezieht.

Die Ergebnisse zeigen, dass die Anzahl der Ladengeschäften in der näheren Umgebung eines Kunden das Verhalten des Kunden bei der Nutzung des Online-Kanals beeinflusst. Erstens reduzieren Ladengeschäfte die Anzahl der Rücksendungen von

Produkten im Online-Kanal. Dieser Effekt wird durch Produkte mit einem höheren wahrgenommenen Risiko für den Kunden verursacht: Ladengeschäfte reduzieren die Anzahl der Rücksendungen für Produkte mit einem höheren wahrgenommenen Risiko (d.h. Produkte mit mehreren Maßen, einem höheren Preis oder ohne Rabatt), beeinflussen aber nicht die Anzahl der Retouren für Produkte mit einem geringeren wahrgenommenen Risiko (d.h. Produkte mit Einheitsmaß, einem niedrigeren Preis oder mit Rabatt). Je nach Art des Produkts können mehr Ladengeschäfte zu 13,91% bis 16,26% weniger Retouren führen, wie eine Simulationsstudie zeigt. Zweitens haben Ladengeschäfte keinen Einfluss auf die Anzahl der Käufe im Online-Kanal. Die Anzahl der Ladengeschäfte in der näheren Umgebung eines Kunden hat keinen Einfluss auf die Anzahl der Warenkörbe, die vom Kunden gekauft werden, oder auf die Anzahl der Produkte, die pro Warenkorb gekauft werden, unabhängig vom wahrgenommenen Risikoniveau der Produkte. Zusammenfassend lässt sich also sagen, dass die Studie in Kapitel 2 einen insgesamt positiven Effekt von Ladengeschäften auf das Kundenverhalten im Online-Kanal zeigt. Während Ladengeschäfte keinen Einfluss auf den Kauf von Produkten im Online-Kanal haben, wirken sie sich andererseits vorteilhaft auf die Rücksendung von Produkten im Online-Kanal aus.

8.2 Einfluss der Versandbedingungen auf Online-Bestellungen und Retouren

Webshops müssen sich für bestimmte Versandbedingungen entscheiden, die festlegen, ob und wann Kunden Versandkosten zahlen müssen. Je nach den Versandbedingungen kann eine Vielzahl von Faktoren (z.B. Bestellgröße oder Produktkategorie) darüber entscheiden, wie viel der Kunde zu zahlen hat. Eine wichtige Überlegung für Einzelhändler ist, dass sich die Struktur der Versandkosten wahrscheinlich auf Rücksendungen und Produktbestellungen auswirkt, da Versandkosten direkt den Preis erhöhen, den Kunden zahlen müssen. Um sicherzustellen, dass die Versandbedingungen der Wirtschaftlichkeit des Online-Einzelhändlers zugute kommt, sollte sie die Zahl der Produktbestellungen erhöhen sowie die Zahl der Rücksendungen verringern (Minnema et al., 2018; Petersen & Kumar, 2015).

Die Studie in Kapitel 3 vergleicht zwei gängige Versandbedingungen hinsichtlich ihrer Auswirkungen auf Produktbestellungen und Retouren im Online-Kanal: (1) eine Versandkostenpauschale, bei der ein fester Betrag für eine Bestellung unabhängig von ihrem Umfang berechnet wird, und (2) einen schwellenwertgebundenen Gratisversand, bei dem eine Gebühr für alle Bestellungen unterhalb eines bestimmten Bestellwerts erhoben wird. Theoretisch kann man davon ausgehen, dass eine Versandkostenpauschale im Vergleich zum schwellenwertgebundenen Gratisversand die Kunden dazu veranlasst, ihre Produktkäufe in weniger und gleichzeitig größere Be-

stellungen aufzuteilen, um dadurch Versandkosten zu sparen. Darüber hinaus kann der schwellenwertgebundenen Gratisversand Kunden dazu veranlassen, so genannte "Füllkäufe" zu tätigen, d.h. Käufe, die den Bestellwert über den Schwellenwert für den kostenlosen Versand bringt. Um die theoretischen Behauptungen zu testen, vergleicht die Studie die beiden Versandbedingungen empirisch - in Bezug auf den täglichen Umsatz, die Anzahl der Bestellungen und Bestellwerte sowie die Anzahl der zurückgesandten Produkte. Die Analyse basiert auf einem umfangreichen Datensatz eines großen europäischen Einzelhändlers, der über 26 Millionen Bestellungen in einer Vielzahl von Kategorien von mehr als 3,8 Millionen Kunden über einen Zeitraum von drei Jahren umfasst.

Die Ergebnisse zeigen, dass die Versandbedingungen das Bestell- und Rückgabeverhalten der Kunden beeinflusst. In Bezug auf das Bestellverhalten zeigt sich, dass der schwellenwertgebundene Gratisversand die Anzahl der Bestellungen erhöht und zu einem höheren Gesamtumsatz führt als eine Versandkostenpauschale. Andererseits ändert sich der Bestellwert durch den schwellenwertgebundenen Gratisversand nicht signifikant. Was das Rücksendeverhalten betrifft, so führt der schwellenwertgebundene Gratisversand zu etwas mehr Rücksendungen als eine Versandkostenpauschale. Dies ist jedoch nicht auf Füllkäufe zurückzuführen, die seltener zurückgegeben werden als reguläre (d.h. Nicht-Füll-)Käufe. Eine Wirtschaftlichkeitssimulation zeigt, dass die positiven Auswirkungen des schwellenwertgebundenen Gratisversands auf das Bestellverhalten der Kunden die negativen Auswirkungen auf das Rücksendeverhalten der Kunden in fast allen betrachteten Szenarien überwiegen und somit der schwellenwertgebundene Gratisversand zu einem höheren Ertrag führt als eine Versandkostenpauschale. Zusammenfassend zeigt die Studie in Kapitel 3 somit, dass der schwellenwertgebundene Gratisversand unter den meisten Umständen profitabler ist als eine Versandkostenpauschale, wobei die höhere Profitabilität aus einem Anstieg der Anzahl der Bestellungen und einem Anstieg des Umsatzes resultiert, auch wenn die Wahrscheinlichkeit von Retouren etwas zunimmt.

8.3 Auswirkungen von Preissenkungen auf Online-Retouren

Viele Einzelhändler ändern ihre Preise dynamisch. Das heißt, viele Einzelhändler passen ihre Online-Produktpreise regelmäßig an, z. B. auf der Grundlage von Nachfrageänderungen, Lagerbeständen und Preisen der Wettbewerber (Elmaghraby & Keskinocak, 2003; Fisher et al., 2018; Grewal, 2011; Grewal et al., 2010). Wenn ein Einzelhändler den Preis eines Produkts senkt, ist der bedeutsamste positive Effekt in der Regel ein Anstieg der Verkaufszahlen (Bijmolt et al., 2005; Gupta, 1988). Preissenkungen können sich darüber hinaus allerdings auch auf die Rücksendequote auswirken.

Wichtig ist, dass die Retouren von zwei verschiedenen Arten von Käufen betroffen sein können. Erstens kann sich das Niveau der Rücksendungen von Käufen, die während einer Preissenkung getätigt wurden (d.h. wenn der Kunde ein Produkt zu einem reduzierten Preis kauft), ändern (Petersen & Kumar, 2009). Zweitens kann sich das Niveau der Rücksendungen von Käufen, die vor einer Preissenkung getätigt wurden (d.h. wenn der Kunde einen höheren Kaufpreis als den nachträglich reduzierten Preis gezahlt hat) und die noch umtauschbar sind, ändern (Bandi et al., 2018).

Die Studie in Kapitel 4 untersucht empirisch, ob Online-Käufe aufgrund einer Preissenkung zum Zeitpunkt des Kaufs/nach dem Kauf (und gleichzeitig während des Rückgabezeitraums) mit größerer oder geringerer Wahrscheinlichkeit zurückgegeben werden. Die Regressionsanalyse mittels eines Survival-Regressionsmodells (Royston & Parmar, 2002) basiert auf einem umfangreichen und außergewöhnlichen Datensatz eines europäischen Online-Einzelhändlers, der mehr als 83 Millionen Einkäufe und mehr als 37 Millionen Retouren in über 300 Kategorien umfasst.

Die Ergebnisse zeigen, dass Preissenkungen Rücksendungen beeinflussen. Die Auswirkung von Preissenkungen auf die Rücksendungen hängt jedoch stark davon ab, ob ein Kunde schon einmal im Preis reduzierte – gleich ob der Rabatt während oder im Anschluss an den Kauf galt – Produkte zurückgegeben hat. Insbesondere bei Kunden, die während oder nach dem Kauf rabattierte Produkte bisher nicht zurückgeschickt haben, führt eine Preissenkung zu etwas weniger Rücksendungen. Bei Kunden, die während oder nach dem Kauf rabattierte Produkte bereits ein Mal zurückgeschickt haben, führt eine Preissenkung dagegen zu etwas mehr Rücksendungen, d.h. der Effekt kehrt sich um. Betrachten wir den letztgenannten Effekt genauer, so zeigt sich, dass der Anstieg hauptsächlich von Kunden stammt, die über mehr Erfahrung mit Rücksendungen haben und während oder nach dem Kauf rabattierte Produkte bereits mehr als zwei Mal retourniert haben. Wichtig ist, dass alle oben genannten Effekte sowohl bei Preissenkungen zum Zeitpunkt des Kaufs als auch bei Preissenkungen nach dem Kauf (und gleichzeitig während des Rückgabezeitraums) auftreten und durchgängig für fast alle Produktkategorien gelten. Bei Suchgütern, Gebrauchsgütern und Geschenkartikeln ist der Effekt jedoch tendenziell geringer. Insgesamt deutet die Studie in Kapitel 4 also darauf hin, dass Preissenkungen Retouren fördern oder hemmen können, wobei die Stärke und Richtung des Effekts von der gewohnheitsmäßigen Reaktion des Kunden auf Preissenkungen bestimmt wird.

8.4 Fazit

Das Omnichannel-Modell birgt für den Einzelhandel eine Vielzahl von Herausforderungen. Zahlreiche Studien haben sich mit den resultierenden Herausforderungen beschäftigt (Bijmolt et al., 2019; Minnema et al., 2018). Die vorliegende Arbeit be-

fasst sich mit drei konkreten Fragestellungen, in denen die bisherige Forschung nur unzureichend aussagekräftig ist. Die Studie in Kapitel 2 zeigt, dass stationäre Ladengeschäfte ein Mittel sind, um Rücksendungen im Online-Kanal zu reduzieren, insbesondere bei Produkten mit einem erhöhten wahrgenommenen Risiko. Darüber hinaus geht der Rückgang der Online-Retouren nicht mit einem Rückgang der Online-Käufe einher. Daher kann es für Online-Einzelhändler von Vorteil sein, neben dem Online-Kanal auch einen Offline-Kanal, d.h. Ladengeschäfte, zu betreiben. Die Studie in Kapitel 3 zeigt, dass die Versandbedingungen von Online-Einzelhändlern Käufe und Retouren beeinflusst. Der schwellenwertgebundene Gratisversand führt zu höheren Umsätzen und mehr Bestellungen, während eine Versandkostenpauschale zu weniger Retouren führt. Wenn man beide Strategien in Bezug auf die Wirtschaftlichkeit vergleicht, ist der schwellenwertgebundene Gratisversand für die meisten Einzelhändler vorteilhafter. Zu guter Letzt zeigt die Studie in Kapitel 4, dass Preissenkungen von Online-Einzelhändlern Rücksendungen beeinflussen. Insbesondere erhöhen Preissenkungen die Anzahl der Rücksendungen von Kunden, die es gewohnt sind, Waren aufgrund von Preissenkungen retournieren, und verringern die Anzahl der Rücksendungen von Kunden, die es nicht gewohnt sind, so zu verfahren. Folglich könnten Online-Einzelhändler davon profitieren, wenn sie Preisnachlässe selektiv für Kunden bewerben, die nicht gewohnheitsmäßig rabattierte Produkte zurücksenden. Kurz zusammengefasst identifiziert diese Doktorarbeit also eine Reihe von praktisch bedeutsamer Faktoren, die einen signifikanten Einfluss auf die Rücksendequoten von Online-Einzelhändlern haben.