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Dissertation

Consumer Behavior in a Multichannel Context and its Managerial Implications

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The dissertation project consists of four papers. Two papers are concerned with multichannel customer behavior: (a) drivers of competitive webrooming and (b) profitability effects of offline channel additions. The remaining two papers deal with consumer reactions towards different website cookie notifications.

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List of Abbreviations

Fig.	Figure
e.g.	for example
i.e.	in other words
US	United States of America
p.	page

Overview of Dissertation Project

In a broad sense, this dissertation project explores antecedents (Article A, Article C, and Article D) and consequences (Article B) of consumer behavior in a multichannel retail context. More specifically, it addresses three main topics: First, it analyzes how consumers choose certain channel-retailer combinations within a competitive (i.e., more than one retailer) multichannel (i.e., more than one channel) context (Article A). Second, it investigates the effects of managerial decisions in a multichannel context (i.e., offline channel addition) on key business figures (i.e., revenue, absolute profit, and profit margin; Article B). Although a managerial decision may, in principle, be made independently of any consumer behavior, its *effect* on key business figures is a function of consumer behavior (i.e., how consumers react to the decision). Therefore, the findings of Article B may also be understood as consequences of consumer behavior. Third, the last two articles (Article C and Article D) focus on one specific channel, the online channel, and investigate consumer reactions to different cookie notifications. The present dissertation, therefore, splits into two major parts (see Table 1). Both parts provide a separate short introduction to each topic and a summary of the corresponding articles is provided.

The first part deals with antecedents of consumer behavior and effects of managerial decisions in a *multichannel* context. By leveraging survey responses referring to consumers' past purchases (Article A) and real transaction data (Article B), this part avoids some of the disadvantages associated with using consumers' articulated behavioral intentions as dependent variables (i.e., poor predictive power for actual behavior; Sheeran and Webb 2016; Rhodes and Bruijn 2013). In this sense, the measurement of the deployed dependent variables should particularly be valid for these articles.

The second part of this dissertation focuses on a specific channel within retailers' multichannel context, the *online channel* (Article C and Article D). The online channel occupies a special position: compared to other channels such as brick-and-mortar stores or catalog, this channel is very young and develops particularly dynamically. In the US, already today, retail e-commerce sales account for roughly 11% of total retail sales (U.S. Department of Commerce 2019). This number is even expected to increase in the future and to extend to other geographies (Young 2019). Therefore, the online channel has become very dominant and is considered as a disruptive development (Christensen and Raynor 2013). The second part of the dissertation utilizes, in total, six experimental studies and a content analysis to assess consumers' reactions to varying cookie notifications and the implementation of the EU cookie regulation, respectively.

This dissertation draws on two main concepts, consumer behavior and multichannel management, which are briefly defined below. Later, the respective articles will introduce other major concepts (e.g., cookie notifications, price fairness). First, throughout this dissertation, consumer behavior comprises not only conative consumer responses, but also cognitive and affective ones. In particular, consumer behavior is understood as "all activities associated with the purchase, use and disposal of goods and services, including the consumer's emotional, mental and behavioral responses that precede or follow these activities." (Kardes, Cronley, and Cline 2011, p. 7). Second, this dissertation considers a channel as consumer contact points, through which the firm and consumers interact. It therefore follows the interpretations of the early multichannel research (e.g., Neslin et al. 2006; Verhoef, Neslin, and Vroomen 2007a) and limits the domain to channels providing a two-way communication, excluding one-way communication channels (e.g., TV; Verhoef, Kannan, and Inman 2015a). Accordingly, multichannel management is "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development" (Neslin et al. 2006, p. 95). The articles within this thesis solely deal with two channels: the online channel (i.e., Web stores) and the offline channel (i.e., brick-and-mortar stores). This focus reflects the current research interest in this field (Verhoef, Kannan, and Inman 2015a) and stems from the fact that the attention of multichannel research has been mainly driven by the extraordinary growth of the online channel (see above) and its implications on firms utilizing traditional offline stores.

The overarching aim of this thesis is to contribute to a better understanding of the complex relationships in a multichannel context. Specifically, it strives to create a more detailed understanding of (a) consumer behavior and (b) consequences of managerial decisions in a multichannel context to enable better-informed managerial decision-making.

Table 1 provides an overview of the four articles that jointly constitute the main body of this dissertation project.

	Article A	**Article B**	**Article C**	**Article D**
Title	What Drives Competitive Webrooming? The Roles of Channel and Retailer Aspects	The profitability of adding bricks to clicks	The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy – The Example of Cookie Notices	The Effect of Privacy Choice in Cookie Notices on Consumers' Perceived Fairness of Dynamic Pricing
Research focus	Multichannel	Multichannel	Online channel	Online channel
Co-Authors	Rico Manß, Katharina Behme	Damian Hesse, Erik Maier, Rico Manß	Lennard Schmidt, Erik Maier	Lennard Schmidt, Erik Maier
Own contribution	Main responsibility: Data analysis Shared responsibility: Theoretical development and writing article	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, writing article	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, data collection, writing article	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, data collection, writing article
Publication status	Published in: The International Review of Retail, Distribution and Consumer Research (VHB-JOURQUAL 3: C)	Under Review in: Journal of Retailing (VHB-JOURQUAL 3: A)	Published in: Journal of Public Policy & Marketing (VHB-JOURQUAL 3: B)	Published in: Psychology and Marketing (VHB-JOURQUAL 3: B) Presented at: the 48th EMAC Annual Conference in 2019

Table 1: Overview of articles

I. Consumer Behavior and Managerial Decisions in a Multichannel Context

1 Introduction

Research on retailing in multichannel systems is an important field in marketing (Verhoef, Kannan, and Inman 2015a). Through technological progress, companies, nowadays, have many channels at their disposal through which they can interact with consumers (Li, Lobschat, and Verhoef 2017). Consumers' reactions, in turn, affect many key business targets such as sales or profit. Thus, to make informed managerial decisions within a multichannel system (e.g., adding or removing a channel), a profound understanding of consumer behavior is crucial.

From this perspective, the multichannel literature is characterized by two major research streams (Verhoef 2012; Shareef, Dwivedi, and Kumar 2016): (a) a consumer stream (demand-side-driven) that deals with consumer behavior in multichannel systems and (b) a company stream (supply-side-driven) that, in a broad sense, investigates effects of managerial decisions in multichannel systems. The consumer stream has specifically focused on topics like channel adoption, channel choice, and channel usage. In contrast, the company stream includes studies that focus on the impact of channels on certain performance metrics as well as how to design the retail mix across different channels. As outlined above, both streams are connected, as, for example, the impact of certain channels on performance metrics are often a function of consumer behavior. This publication-based dissertation aims to contribute to both streams (consumer and company stream) with one article each.

Consumer stream:

In the past, many studies on multichannel consumer behavior focused on consumers' channel choice (e.g., Wang et al. 2016; Vasiliu et al. 2015; Gensler, Verhoef, and Böhm 2012; Rhee 2010; Mcgoldrick and Collins 2007; Verhoef, Neslin, and Vroomen 2007a; Noble, Griffith, and Weinberger 2005; Youn-Kyung Kim, Soo-Hee Park, and Pookulangara 2005; Reardon and McCorkle 2002), that is, consumers' decision for a particular channel within a purchasing process. Within a given purchasing process, the combination of consumers' channel choice (e.g., online vs. offline) and the moment of this choice (e.g., during searching vs. purchasing) creates a plane of possible behavior patterns (e.g., showrooming, webrooming) in a multichannel system. Showrooming, the behavior pattern of searching for a product offline but purchasing it online, was perceived as a particular threat to traditional brick-and-mortar retailers and, therefore, attracted notable attention from research. Studies investigated drivers and characteristics of consumers who perform showrooming (Kokho Sit, Hoang, and Inversini 2018; Li et al. 2018; Ting Zhang et al. 2018; Daunt and Harris 2017; Gensler, Neslin, and Verhoef 2017; Rejón-Guardia and Luna-Nevarez 2017; Orús, Gurrea, and Flavián 2016) as well as implications and potential counterstrategies for retailers (Bing Jing 2018; Kuksov and Liao 2018b; Mehra, Kumar, and Raju 2018; Basak et al. 2017; Gu and Tayi 2017; Rapp et al. 2015; Balakrishnan, Sundaresan, and Zhang 2014). In contrast, webrooming, the pattern of searching for a product online but purchasing it offline, has received considerably less attention (Flavián, Gurrea, and Orús 2016) and been identified as an important field for future research (Verhoef, Kannan, and Inman 2015a). Webrooming is an increasingly common behavior pattern in multichannel environments (Criteo S.A. 2017) with potentially negative consequences for retailers (Mehra, Kumar, and Raju 2013). It is particularly detrimental for retailers when it is accompanied by a switch of retailer because the latter incurs costs for providing product information, stock and online support without generating corresponding sales (Chiu et al. 2011; van Baal and Dach 2005).

Despite its managerial relevance, research has devoted little attention to webrooming in conjunction with a potential simultaneous switch of retailer. Thus, this publication-based dissertation aims to address this research gap with Article A. In particular, the research objective of Article A is to empirically examine the drivers of webrooming in combination with a switch of retailer by incorporating aspects of retailers and channels in one framework.

Company stream:

This literature stream primarily deals with the effects of managerial decisions on certain, mostly business-related objective functions (e.g., sales or profit). A fundamental managerial decision within a multichannel system is to add a channel. It is, therefore, not surprising that this question was and still is particularly relevant for research in this area (Verhoef, Kannan, and Inman 2015a). Despite the popularity of this question, the majority of research has been limited to the impact of channel additions on companies' sales (Zhang et al. 2010), whereas, the effect of channel additions on *retailers' profitability and profit* *margin*, key business figures, remains unknown. Yet, changes in profitability and profit margin, are likely to occur, for instance as sales costs differ by channel, as channel availability affects return rates or as the product and customer mix may change as a result of the channel addition. Investigating the profitability effect of channel additions, therefore, has been identified as an important area for future research (Avery et al. 2012a; Pauwels and Neslin 2015a). Article B aims to respond to these calls for research and to investigate the profitability effect of adding bricks to clicks, that is, the opening of brick-and-mortar stores in addition to an online shop.

2 Present Research Project

2.1 Overview of Articles

	Article A	**Article B**
Title	What Drives Competitive Webrooming? The Roles of Channel and Retailer Aspects	The profitability of adding bricks to clicks
Research focus	Multichannel	Multichannel
Co-Authors	Rico Manß, Katharina Behme	Damian Hesse, Erik Maier, Rico Manß
Own contribution	Main responsibility: Data analysis Shared responsibility: Theoretical development and writing article	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, writing article
Publication status	Published in: The International Review of Retail, Distribution and Consumer Research (VHB-JOURQUAL 3: C) Manss, R., Kurze, K., & Bornschein, R. (2019). What drives competitive webrooming? The roles of channel and retailer aspects. The International Review of Retail, Distribution and Consumer Research. https://doi.org/10.1080/09593969.2019.1687104	Under Review in: Journal of Retailing (VHB-JOURQUAL 3: A)

Table 2: Overview of articles – Part I of the dissertation

2.2 Summary Article A

Research motivation and objective: Although webrooming poses a considerable risk to retailers (Chiu et al. 2011; van Baal and Dach 2005) and its drivers can differ from those of other forms of research shopping (e.g., showrooming; Orús, Gurrea, and Flavián 2016), only a few studies investigate this phenomenon. Even fewer studies address webrooming in conjunction with a potential simultaneous switch of retailer, despite its managerial relevance. Thus, our research objective is to empirically examine the drivers of webrooming in combination with a switch of retailer by including aspects of retailers and channels in one framework. This approach is novel and responds to previous calls to address this important research gap (Ehrlich 2011; Verhoef, Neslin, and Vroomen 2007a).

Methodology: We surveyed 1,081 retail customers about their most recent consumer electronic product purchase and analyzed their responses using various statistical methods (e.g., confirmatory factor analysis and baseline-category logit models).

Main findings: We found three channel aspects (i.e., quality, after-sales service, and price) and two retailer aspects (i.e., assurance of delivery and retailers' price attractiveness) to be significant predictors of customer behavior patterns comprising channel loyalty (i.e., loyal online shopping and competitive online shopping) and retailer loyalty (i.e. loyal webrooming, loyal online shopping) respectively. In addition, we revealed two interaction effects between channel and retailer aspects: composure compensation and price enticement. Composure compensation refers to the fact that a high level of assurance of delivery dampens the impact of a channel's after-sales service on the probability of competitive webrooming. In a similar vein, very attractive retailer prices can dampen the impact of channel-related after-sales service, which we refer to as price enticement.

Contribution: In our work, we combine channel and retailer switching aspects into one framework. In this context, we introduce a matrix of customer behavior patterns, which provides a theoretical framework to better structure behavior patterns in this research field. The dual emphasis on channel and retailer aspects not only allows us to investigate subsets of previously examined shopping behavior patterns (i.e., competitive webrooming), but also enables us to empirically examine their interplay, as it occurs in real life shopping situations.

2.3 Summary Article B

Research motivation and objective: In recent years, many retailers have been integrating new sales channels to their channel footprint hoping to generate additional sales (e.g., Allbirds', Bonobos, Casper). Yet, the effect of channel additions on *retailers' profitability and profit margin* remains unknown. While absolute profits are likely to grow with revenue, a profit margin effect might depend on channel sales-related costs, product mix, return levels, or the behavior of existing or new customers. Consequently, investigating the profitability effect of channel additions is characterized as a "fruitful area for future research" (Verhoef, Kannan, and Inman 2015b, p. 177) and a top priority on retailing's research agenda (Avery et al. 2012b; Pauwels and Neslin 2015b). This research investigates the profitability effect of adding bricks to clicks, that is, the opening of a brick and mortar store in addition to an online shop.

Methodology: We obtained data from a large European multichannel retailer, which opened its first brick-and-mortar store in 2016. To assess the profitability effect of the offline channel addition, we used a quasi-experimental design and compared observations aggregated to a treatment area (with store opening) with matched control regions in a difference-in-difference approach, similar to extant research on channel additions (e.g., Avery et al. 2012b; Huang, Lu, and Ba 2016; van Nierop et al. 2011). In addition, we estimated an individual level data finite mixture model (FMM) to understand potentially unobserved heterogeneity among different segments of existing customers with respect to their reactions to the store opening.

Main findings: We found the offline channel addition to increase both revenue and absolute profit, but to reduce the profit margin in the short run. The paper establishes four drivers for this effect: (1) differences in the sales-related costs between the on- and offline channels create an initial profit margin decline after the store opening, which is only redeemed over time; however, (2) the return quota declines, (3) consumers purchase more sensory products in and around the store, and (4) new customer purchases increase in and around the store – all of which increase the profit margin. Furthermore, we found the profitability effect of adding a physical store varies by the segment of existing customers: it has a highly positive, but short-lived, effect on customers very active prior to the store opening (possibly because these customers are highly involved with the retailer), while other customer segments are less strongly affected.

Contribution: Article B contributes to the multichannel literature by adding a new dimension to the discussion on offline channel additions: profitability. In particular, it is the first article to empirically show profitability effects of a store opening, establish drivers of these effects, and investigate segment-specific effects of channel additions for profitability. Extant research has addressed those questions on a sales basis only (e.g., Avery et al. 2012a; Pauwels and Neslin 2015a; Pauwels et al. 2011a).

3 Article A: What Drives Competitive Webrooming? The Roles of Channel and Retailer Aspects

Abstract

Competitive webrooming, the phenomenon in which consumers gather product information online but ultimately purchase the product in an offline store of a competing retailer, has gained traction and become a major threat for retailers. To gain a deeper understanding of its drivers, we surveyed 1,081 retail customers about their most recent consumer electronic product purchase to examine the impact of channel-related aspects as well as retailer-related aspects – a dual approach that has not been applied by extant literature. A channel's anticipated after-sales service and price level are the strongest predictors for webrooming. Moreover, retailer aspects determine whether customers simultaneously switch the retailer when webrooming. A retailer's assurance of delivery, including payment modalities, return policies, and product obtainment, as well as competitive product prices motivate consumers to switch the retailer when webrooming. These results suggest that customers have a fundamental need for certainty within and after the buying process, which can be satisfied by both channel and retailer. Additionally, this is the first study to empirically test for interactions between channel and retailer aspects, as they are likely to occur in real shopping situations. We identified two interactions: First, a retailer's assurance of delivery can compensate for an anticipated lack of a channel's after-sales service, dampening the impact of the latter on competitive webrooming. Second, also a retailer's price attractiveness acts in a similar vein. Hence, to steer customers into channels and/or keep them with the company, retailers should emphasize their price attractiveness as well as assurance of delivery.

Publication status

Published in: The International Review of Retail, Distribution and Consumer Research (VHB-JOURQUAL 3: C)

Manss, R., Kurze, K., & Bornschein, R. (2019). What drives competitive webrooming? The roles of channel and retailer aspects. The International Review of Retail, Distribution and Consumer Research.

https://doi.org/10.1080/09593969.2019.1687104

4 Article B: The Profitability of Adding Bricks to Clicks

Abstract

Many e-commerce retailers are adding brick and mortar stores to their channel system. Although research has established the positive revenue effect of these store additions, the effect on profitability is unknown. While absolute profits are likely to grow with revenue, a profit margin effect might depend on channel sales-related costs, product mix, return levels, or the behavior of existing or new customers. The present research establishes that adding bricks to clicks increases profits absolutely, but reduces the profit margin in the short run. We find four drivers for this effect: (1) differences in the sales-related costs between the on- and offline channels create an initial profit margin decline after the store opening, which is only redeemed over time; however, (2) the return quota declines, (3) consumers purchase more sensory products in and around the store, and (4) new customer purchases increase in and around the store – all of which increase the profit margin. Furthermore, we find the profitability effect of adding a physical store varies by segment of existing customers: it has a highly positive, but short-lived, effect on customers very active prior to the store opening (possibly because these customers are highly involved with the retailer), while other customer segments are less strongly affected. Our findings, therefore, extend the revenue-based cross-channel elasticity matrix to profitability and offer guidance for retailers considering introducing a physical store.

Keywords: *Offline channel addition, bricks to clicks, profitability, omnichannel*

Publication status

Under Review in: Journal of Retailing (VHB-JOURQUAL 3: A)

1 Introduction

In recent years, many e-commerce pure players have added offline channels, hoping to generate additional sales (e.g., Allbirds, Bonobos, Warby Parker). While research agrees on the positive revenue effect of channel additions (Li, Lobschat, and Verhoef 2017), the effect on profitability remains unknown. Anecdotal evidence shows different profitability effects: the former online pure player Bonobos, for instance, remained unprofitable despite (or maybe because of) opening almost 50 stores since 2013 (Wall Street Journal 2019). In contrast, other e-commerce retailers that have added brick-and-mortar stores seem to be thriving, as their profit margin improved after opening new store locations (e.g., Warby Parker broke even in 2018 after opening 65 stores; New York Times 2018). Consequently, it is vital for managers to understand what profit margin effects to expect before engaging in a far-reaching strategic decision such as a channel addition, as well as which drivers most strongly affect the profit margin of their channel system.

The profitability effect of channel additions is by no means trivial. Although *absolute profits* are likely to increase along with the growing revenues of a channel addition, the *profit margin* may be either positively or negatively affected. On the one hand, sales-related costs might differ, rendering it relatively more profitable to sell in one versus another channel and influencing the profit margin as the channel mix changes. Store sales costs (e.g., rent, staff costs), for instance, are likely to exceed online sales costs (e.g., online marketing, logistics; Kuksov and Liao 2018a) – at least at the beginning when a store is yet unknown. On the other hand, the ability to touch and test products in a store could lower a retailer's return rates (Ofek, Katona, and Sarvary 2011), lead to more frequent purchases of sensory products (Pauwels and Neslin 2015b), and attract new customer segments to the store (Avery et al. 2012b) – all of which are likely to yield a higher profit margin. Furthermore, the profit margin effect might differ by customer segment (e.g., power shoppers are more reactive to channel additions; Ward 2001). Consequently, extant research characterizes investigating the profitability effect of channel additions as a "fruitful area for future research" (Verhoef, Kannan, and Inman 2015b, p. 177) and a top priority on retailing's research agenda (Avery et al. 2012b; Pauwels and Neslin 2015b). This demand has, to the best of our knowledge, not yet been met. We, therefore, investigate the absolute and marginal profitability effect of adding bricks to clicks, that is, the opening of a brick-and-mortar store in addition to an online shop.

Analyzing aggregated sales data from a physical store addition to a large European retailer's online shop over a period of two years in a quasi-experimental design, we replicate the positive revenue effect of store additions (one year after the store opening: +27.0% in the regions around the store compared with control regions) established in extant research (Pauwels and Neslin 2015b; Avery et al. 2012b). As expected, absolute profits increase with revenue growth (+48.3%). Opening a brick-and-mortar store increases profit margin in the long run (+2.2 percentage points). However, the profit margin decreases in the short run (−1.8 percentage points) and only turns positive over time (24 weeks after the opening). Three drivers influence this profit margin effect positively: a decreased return rate, an increased share of sensory products, and newly won customer segments improve the profit margin; one driver, the higher sales-related costs of the brick-and-mortar store, initially affect the profit margin negatively, although this effect diminishes over time. Amongst existing customers, a latent class analysis shows that various customer segments react differently to the store opening, in that the profit increases most strongly for a small share of power shoppers (<20% of customers), as they visit the new store immediately. In summary, this research contributes to the literature by (1) being the first to establish the profit margin effect of offline channel additions and (2) identifying positive (lower return rate, sensory product share, new customers) and negative (channel share and sales-related costs) drivers of the effect. Further, we (3) show that the profitability effect is segment specific.

2 Literature and Conceptual Foundations

2.1 Literature on Channel Additions

Extant research has extensively investigated the effect of channel additions between complementarity and cannibalization (Weltevreden 2007), assessing various cells in the cross-channel elasticity matrix (see Table 1). However, to date no empirical research has examined the effect of channel additions on profitability. Although some analyses in a multichannel environment do touch on the subject, they are not informative for retailers in their decision to open another channel. Moreover, these analyses do not differentiate between absolute and marginal profitability: Kumar et al. (2006) only establish the profitability of a multichannel customer segment in general; Kuksov and Liao (2018a) model how brick-and-mortar retailers might extract a profit share from manufacturers interested in a multichannel presentation of their products but do not cover channel additions; and Grewal et al. (2017) discuss profitability as consequence of analytical or operational excellence across channels but do not investigate it. Research in a service setting shows that selling restaurant food on a service platform affects absolute restaurant profits in line with an overall sales increase (Zhang, Pauwels, and Peng 2019), but these findings cannot be transferred to a retail setting (e.g., because although the order is placed differently [vs., e.g., by phone], it still served from the same restaurant, not a different channel). Consequently, investigating the profitability effect of channel additions is often described as "crucial area for future research" (Pauwels and Neslin 2015b, p. 195; see also Avery et al. 2012b; Verhoef, Kannan, and Inman 2015b). This research aims to close this gap by assessing the effect of adding bricks to clicks on a retailer's profit margin.

Moreover, for retailers it is critical to know not only whether opening a store affects their profitability but also, if so, through which drivers. Multiple revenue drivers of channel additions have already been established in extant research on channel additions (e.g., purchase frequency: Pauwels and Neslin 2015b; basket size: van Nierop et al. 2011), but no profit margin drivers have been tested. Similarly, extant research investigates segment-specific effects of channel additions only for revenue (Pauwels et al. 2011b) and not for profitability.

	Effect on:		
Article	**Revenue**	**Profits**	**Channel additions**
Ansari, Mela, and Neslin 2008	✓	–	▪ Online to catalogue
Gensler, Dekimpe, and Skiera 2007	✓	–	▪ Online to catalogue
Dholakia, Zhao, and Dholakia 2005	✓	–	▪ Online to catalogue and brick-and-mortar
Pauwels et al. 2011b	✓	–	▪ Online to brick-and-mortar
van Nierop et al. 2011	✓	–	▪ Online to brick-and-mortar
Avery et al. 2012b	✓	–	▪ Brick-and-mortar to online and catalogue
Pauwels and Neslin 2015b	✓	–	▪ Brick-and-mortar to online and catalogue
Wang and Goldfarb 2017	✓	–	▪ Brick-and-mortar to online
Bang et al. 2013	✓	–	▪ Mobile to online
Huang, Lu, and Ba 2016	✓	–	▪ Mobile to online
Grewal et al. 2018	✓	–	▪ Mobile to store
Wang, Malthouse, and Krishnamurthi 2015	✓	–	▪ Mobile to online
Intended contribution	✓	✓	▪ Brick-and-mortar to online

Table 1 (B): Extant literature on retail channel additions

2.2 From Revenue to Absolute Profits and Profit Margins

To assess the profitability effect of retail channel additions, we must first distinguish between various profitability levels (see Table 2: [I]–[III]). Retailers commonly use gross sales, that is, revenue generated before product returns, as their base indicator. Retailers also report net sales, which are gross sales minus the returned products (Avery et al. 2012b; for a reporting example, see Wayfair 2019). Profit is generally defined as “the total of income less expenses, excluding the components of other comprehensive income” (IAS 1.7 2018). The simplest measure of profitability level is gross profits ([I], e.g., Zalando 2019), which is net sales minus the cost of goods sold. Gross profits are strongly influenced by the product mix (through cost of goods sold) but are independent of the channel-specific sales-related costs.

Therefore, gross profits are too narrow to assess profitability of a store opening, so herein we focus on *operating profit* ([II]; sometimes also termed “operating income”: Subramanyam and Wild 2009) as a more comprehensive measure because it accounts for sales-related costs (e.g., logistics, digital marketing, store operations). This compares with managerially used constructs such as “contribution profit”, which subtract sales-related logistics (e.g., Westwing 2019) or marketing expenses (e.g., Netflix 2019). Operating profit should also be influence by channel-specific sales-related costs, such as logistics or store operations, which influence profitability through the changing channel mix. Further, channel sales-related costs are indirectly influenced through customer return behavior and the customer mix.

Although even more comprehensive measures of profitability assessment [III], such as earnings before interest and tax (EBIT), exist, they are not meaningful in this context, as an EBIT assessment subtracts cost components that are shared between channels, such as general and administrative or research and development expenses. These shared costs are not directly sales and channel related but rather based on a management rule of cost allocation; therefore, they should not be directly affected by the channel addition (except, e.g., through fixed-cost degression).

Level	*Absolute Indicator*	*Relative Indicator*	*Theoretical Drivers*
	Gross sales		Product mix, customer mix
	- Returns	Return rate	Product returns
	Net sales		
	- Costs of goods sold		Product mix, customer mix
[I]	**Gross profit**		
	- Sales-related costs (e.g., on- and offline advertising, store operations, logistics)		Channel share and channel sales-related costs, product returns, customer mix
[II]	**Operating profit**	**Operating margin**	
	- Overhead costs, research, etc. - Other non-sales-related costs		
[III]	**EBIT**	**EBIT margin**	

Table 2 (B): Absolute and relative profitability indicators at different levels.

In addition to determining the profitability level, it is crucial to distinguish between *absolute* and *relative profitability*. It is highly probable that absolute profits will increase or decrease in tandem with changing revenues. Relative profitability (i.e., the profit margin), in contrast, depends on the operating model of the different channels (e.g., sales-related costs, product mix, return costs, new vs. loyal customers). Therefore, we focus on investigating the *operating profit margin* (hereafter: profit margin), that is, the operating profit's share of the gross sales.

3 Hypotheses

We suggest that four drivers affect the profit margin of brick-and-mortar channel additions: channel mix and the associated channel sales-related costs, product returns, product mix, and the share of new customers. Fig. 1 summarizes our conceptual model and the related hypotheses, with theoretical constructs in boldface and measurement variables in parentheses. The four drivers should comprehensively address profit margin effects of channel additions, as they directly influence the different cost components (see Table 2) and are the most frequently discussed revenue effects of channel additions (e.g., Bang et al. 2013; Pauwels et al. 2011b; Pauwels and Neslin 2015b).

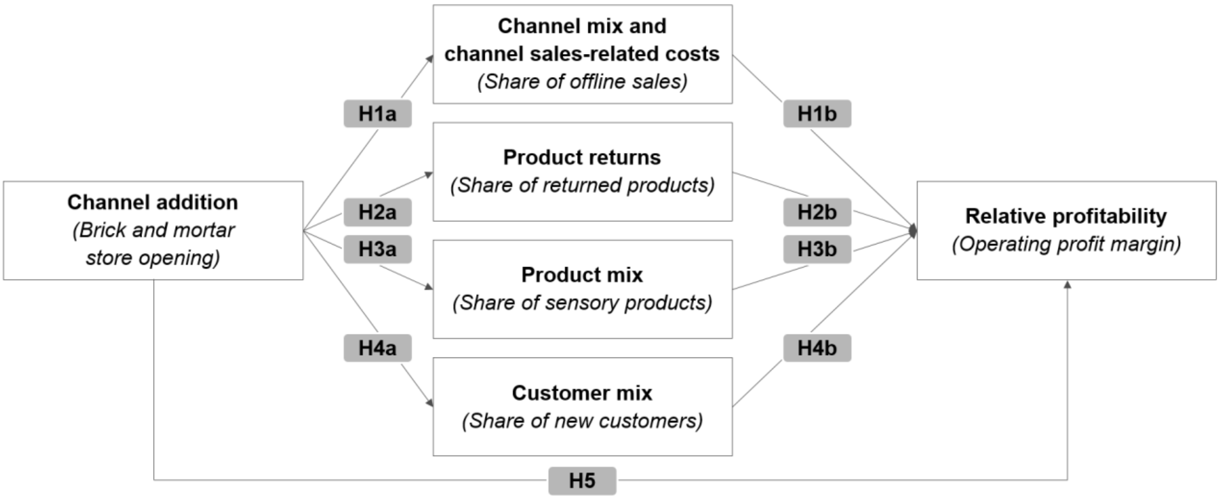

Fig. 1 (B): Conceptual model with key constructs in boldface and measurement variables in parentheses

3.1 Channel Share and Sales-related Costs

The mix of existing versus new channels and their relative sales-related costs will strongly influence a retailer's profit margin (Avery et al. 2012b): if a greater share of sales is generated in a channel with higher (lower) sales-related costs, the profit margin will decrease (increase). The effect of opening a brick-and-mortar store on the share of offline sales is trivial: it will necessarily increase, although potentially not immediately. Extant research shows that after one to two years, new offline stores typically reach a sales level between 30% (Pauwels and Neslin 2015b) and 60% (Wang and Goldfarb 2017) of total sales in the regions where they open. Formally, we propose:

H1a: The introduction of a brick-and-mortar store increases the share of offline sales.

The effect of a higher offline share on the profit margin, in contrast, is less intuitive. Sales-related costs arise in both online (e.g., online marketing, logistics) and brick-and-mortar stores (e.g., rent, staff costs). Popular opinion holds that offline shops have lower profit margins – either from their higher sales-related costs, such as staff and rent (Financial Times 2019) or through the need to lower prices to the level of cheaper online shops (HRC Advisory 2016). In line with these opinions, extant research suggests, though does not test, that the higher fixed costs of a store reduce profit margins (Kuksov and Liao 2018a).

Also different arguments on channels' sales-related costs exist, however: First, customer acquisition on the internet is becoming increasingly expensive (Analytic Partners

2017), which increases sales-related costs and reduces retailers' online profit margin. Second, some doubt exists that online sales-related costs are always lower (Rigby 2014), especially in product categories that are costly to ship or return-heavy (e.g., apparel, CNBC 2017). That said, in the short to medium term, the high fixed costs of a store (i.e., rent and staff) are likely to be high relative to sales, as sales will only increase over time. Therefore, we expect the share of offline sales to negatively influence profitability, although this negative effect is likely to decrease over time. Formally, we propose the following novel hypothesis:

H1b: A higher share of offline sales in the overall channel mix decreases the profit margin.

3.2 Product Returns

Increasing the number of channels through which a consumer can investigate products may reduce the share of returned products. Generally, research shows that multichannel customers have lower return rates (Kumar and Venkatesan 2005), as returns may decrease when consumers have the ability to use another channel: especially the addition of bricks to clicks might have a positive effect on return rates, as consumers can touch and test the products (Avery et al. 2012b), which lowers their purchase risk (Balasubramanian, Raghunathan, and Mahajan 2005), especially for sensory items (Betancourt et al. 2016). In line with these findings, in-store return rates are much lower than online return rates (e.g., ~9% vs. ~30% according to industry estimates: Invesp 2019). Furthermore, the need to lower returns could also be an explicit motivation for a retailer to open a brick-and-mortar shop (in addition to its online store) or increase the service levels of existing physical stores (after adding an online shop, where returns matter; Ofek, Katona, and Sarvary 2011). In line with this reasoning, Pauwels and Neslin (2015b) find that opening a store reduces return rates in the mail order channel (albeit catalogue, not online), although customers increasingly used the store to return products. Formally, we hypothesize the following in replication of extant research:

H2a: The introduction of a brick-and-mortar store decreases the share of returned products.

The negative profit margin effect of high return rates is widely accepted (e.g., Hjort and Lantz 2016; Guide et al. 2006; Minnema et al. 2016), although there might be an optimum level to which return levels should be reduced (Petersen and Kumar 2009). Returns are associated with multiple costs, such as collection, refurbishment, and depreciation costs (Ofek, Katona, and Sarvary 2011). If retailers can reduce return rates without measures that prevent customers from repurchasing, for instance, by opening a store that would enable customers to test the products, their profits should increase. Conversely, an increase in return rates is likely to hurt the profit margin. Consequently, we hypothesize the following:

H2b: A lower share of returned products through the introduction of a brick-and-mortar store increases the profit margin.

3.3 Product Mix

Consumers might use a channel for purchasing specific, potentially more profitable, products, due to the channel's inherent capabilities (Avery et al. 2012b; Bang et al. 2013). For instance, Huang et al. (2013) show the products customers tend to purchase in mobile shops are time critical but do not require substantial information research prior to purchasing. A key advantage of brick-and-mortar (vs. online) stores is customers' ability to touch and try the product (Avery et al. 2012b), which lowers a product's performance risk (Verhoef, Neslin, and Vroomen 2007b). This also relates to the distinction between high- and low-touch products (Lynch, Kent, and Srinivasan 2001). Consequently, consumers tend to use stores to purchase products that are sensory (vs. nonsensory: Pauwels et al. 2011b; Betancourt et al. 2016). We, therefore, suggest the following in replication of extant research:

H3a: The introduction of a physical store increases the share of sensory products.

Sensory products are likely to have a higher profit margin than nonsensory products for three reasons. First, touching the product is likely to positively affect product evaluation. Specifically, touching the product might create a loss aversion–based endowment effect (Kahneman, Knetsch, and Thaler 1991), which is likely to increase the evaluation of the touched product (Tom, Lopez, and Demir 2006). Second, the ability to touch the product should reduce consumers' perceived risk, which is an additional value component that translates into higher willingness to pay or greater purchase intention at a given price (Park, Lennon, and Stoel 2005; Okada 2010). These two drivers enable retailers to charge higher prices or sales-staff to upsell, which in turn increase profit margins. Third, because sensory products are more difficult to purchase with pure online research, we can assume that they face less price pressure and should consequently offer higher profitability. Formally, we make the following novel suggestion:

H3b: The increase in the share of sensory products through an offline channel addition increases the profit margin.

3.4 Customer Mix

Different retail channels are attractive to different customer segments (Fürst, Leimbach, and Prigge 2017; Coelho, Easingwood, and Coelho 2003), which results in segment-specific channel usage behavior in multichannel systems (Pauwels et al. 2011b; Gensler, Dekimpe, and Skiera 2007). Consequently, opening a new channel type will bring new customers in contact with the retailer. Specifically, a brick-and-mortar store may attract customers who favor shopping in stores and are more hesitant with regard to online channels (Avery et al. 2012b). Formally:

H4a: The introduction of a physical store increases the share of new customers.

Customers newly acquired through a brick-and-mortar store might be more profitable for three reasons. First, customers who prefer brick-and-mortar stores to online stores are different in terms of shopping orientation, focusing on tangible and communicative aspects of a shopping experience (Schramm-Klein, Swoboda, and Morschett 2007), and might be less price sensitive than online shoppers (as the latter tend to be disloyal and migrate across websites: Ansari, Mela, and Neslin 2008). Second, offline shopping is associated with lower perceived risk in terms of privacy, purchase, or transaction security (Eggert 2010), which might increase willingness to pay for those customers acquired in brick-and-mortar stores. Third, the newly acquired customers are potentially attracted through sensory products in the brick-and-mortar store, which have higher profitability (see H3b). Consequently, we make the novel suggestion:

H4b: The increase in the share of new customers through an offline channel addition increases the profit margin.

In summary, the different effects of a channel addition point towards an increased profit margin. Although the effect of the channel mix and the associated channel sales-related costs likely reduces the profit margin in the short run, all other drivers (returns, product mix, and customer mix) are likely to increase the profit margin. Formally, we thus summarize with the following novel hypothesis:

H5: The introduction of a brick-and-mortar store increases a retailer's profit margin.

3.5 Existing Customers: Segment-specific Reaction

Adding a physical store might, however, affect existing customers differently. For instance, store additions might increase the loyalty of only certain segments of existing customers, who, in turn, could also adjust their return behavior or purchase different products. This matters for retailers, because they need to identify the most efficient sales channel per customer segment (Inman, Shankar, and Ferraro 2004). Specifically, they could open stores in regions with favorable characteristics of existing customers (e.g., where the most or least loyal customers live). Across all existing customer segments, we expect an availability effect of the store opening as customers come into contact more frequently with the brand (Baxendale, MacDonald, and Wilson 2015). For multiple reasons, an additional effect is likely to arise for highly involved customer segments. First, these customers are more likely to notice a channel addition (i.e., a new store), as they are likely to follow that retailer's communication more closely (e.g., through customer relationship management). Second, their activity in the past likely increased their purchase capabilities with the retailer, which renders them more prone to quickly adopt a new channel (Ward 2001). Third, experienced customers are also likely to be more highly involved with the product category overall (e.g., fashion lovers) and are, thus, more likely to utilize the different capabilities that a channel addition offers. Finally, because loyal customers have spent more money in the past, they are likely more profitable in the channel addition as well. Formally:

H6: The most active existing customers show the strongest positive profitability effect of the channel addition.

4 Data Description

We obtained data from a major European multichannel retailer selling fashion and lifestyle products (category not more closely specified upon request of the retailer). The company is one of the largest retailers of its category in its market of operation. Initially, the retailer sold products solely via its online store before opening its first brick-and-mortar store. The retailer now operates more than ten stores in addition to its online store, but sales from the online channel still substantially exceed brick-and-mortar sales.

Our analysis investigates the profitability effect of the first store opening. We received individual-level transaction data for a period of one year before and one year after the channel addition. In line with extant research (e.g., Pauwels and Neslin 2015b), we aggregate the data for a comparison of the overall effect (quasi-experimental design with matching). In addition, we use individual data for calculating segment-specific effects among existing customers (customer-level latent-class analysis).

The data set includes customer transaction-level data for one year before and one year after the store opening, which provides a balanced time interval (store opening ± 51 weeks). Our analysis period of 102 weeks is comparable to previous studies of channel additions (ranging from 47 [van Nierop et al. 2011] to 208 weeks [Ansari, Mela, and Neslin 2008]. We used this period and specific store addition because throughout this period the retailer did not open any other physical stores and no major changes occurred in the competitive landscape of the market (e.g., bankruptcy or entry of competitors) or store location (e.g., new store of competitor opening). Moreover, there were no major legal changes that affected the retailer (as part of the products are covered by insurance plans). It is also important to note that during the 102 weeks of our study, the retailer did not apply any locally customized marketing or pricing campaigns, only pursuing a national marketing plan.

	Before Store Opening					**After Store Opening**				
Variable	**Treatment Zip Codes (n = 114)**		**Remaining Zip Codes (n = 10,038)**		**Ratio**	**Treatment Zip Codes (n = 114)**		**Remaining Zip Codes (n = 10,029)**		**Ratio**
	Mean	SD	Mean	SD	Value	Mean	SD	Mean	SD	Value
Gross sales per customer	894.43	(113.75)	1,016.41	(7,813.35)	.88	1,046.57	(508.68)	1,082.74	(7,390.68)	.97
Operating profit per customer	41.20	(28.90)	73.72	(216.90)	.56	75.39	(72.67)	93.10	(542.59)	.81
Share offline sales[a]	0	0	0	0	n/a	.17	(.10)	<.01[c]	(.06)	28.67
Share returns[a]	.34	(.07)	.32	(.22)	1.09	.31	(.06)	.33	(.21)	.96
Share sensory products[a]	.69	(.07)	.72	(.25)	.97	.75	(.06)	.74	(.25)	1.02
Share new customers[b]	.43	(.05)	.47	(.24)	.90	.46	(.05)	.44	(.24)	1.06

[a]Measured as share of sales; [b]Measured as share of new customers on total number of customers; [c]Customers travelling across zip codes to the store to purchase

Table 3 (B): Descriptive statistics of the performance variables on zip code level

For 2,497,373 orders of 1,256,911 unique customers, we observed gross sales, returns, cost of goods sold (COGS), logistics costs, and sales-related costs (i.e., marketing, store rent, and store staff costs). To conceal the actual sales data, the retailer applied a multiplier to all financial components of an order. Absolute effects, therefore, are measured in monetary units (MUs). The anonymized data set also provides the specific product that was ordered (used to classify sensory vs. nonsensory products, based on a prestudy[1]), zip code for the place of residence, customer status (i.e., new vs. repeated customer), and the channel in which the order was placed (online store vs. offline store). We measured COGS by order. Sales-related costs have two components: logistics costs are measured by order (0 for offline purchases), and other sales-related costs are allocated: we sum all non-logistics sales-related costs (online marketing, rent, and staff costs) and divide this value by the number of purchases in that period. Table 3 provides an overview of the key variables in our model before and after the store opening, based on an aggregation by zip code – our unit of analysis.

5 Methodology

5.1 Overall Effect: Quasi-experimental Design with Matching

To assess the profitability effect of opening a brick-and-mortar store, we use a quasi-experimental design and compare observations assigned to a treatment area (with store opening) with observations assigned to matched control regions in a difference-in-differences approach, similar to extant research on channel additions (e.g., Avery et al. 2012b; Huang, Lu, and Ba 2016; van Nierop et al. 2011). The major advantage of this approach is that we are able to control for unobserved effects that coincide with the store opening, such as general economic recessions, seasonal variations, and changes in the popularity of specific products, as both the treatment and control regions would experience such events (Angrist and Pischke 2009; Avery et al. 2012b). Consequently, difference-in-differences estimators based on a matching with control regions are also discussed as a means to address potential endogeneity concerns (Germann, Ebbes, and Grewal 2015; Tirunillai and Tellis 2017).

For the outlined research design, three general validity concerns may remain. First, a store selection bias could be in play, such that the retailer's management strategically selects

[1] A prestudy showed that for a group of products (e.g., sunglasses and other accessories), consumers perceived a high need for touch (Lynch, Kent, and Srinivasan (2001), which is associated with sensory products ($M_{sensory} = 4.24$), while they perceived low need for touch for a second group (nonsensory products: e.g., cleaning products) ($M_{nonsensory} = 1.43$; $t = 12.58$, $p < .001$).

attractive regions for a store opening. This would imply that, even prior to the actual store opening, customers in such regions differ from other customers in terms of variables management perceives as important. Yet, such absolute differences in key variables prior to store opening do not pose a bias in a difference-in-differences approach, as this approach only compares the development of the differences between the control and treatment groups (Angrist and Pischke 2009; Wooldridge 2012). Second, self-selection on the customer level could bias the results, such that customers cause the effects in the control or treatment group. This problem is frequently discussed with regard to omnichannel technology adoption (i.e., only some customers adopt a new channel, such as mobile commerce or tablet computers; Huang, Lu, and Ba 2016; Ghose, Han, and Xu 2013). Self-selection, however, should not be an issue in our case, because the comparison is based on regions into which self-selection is unlikely (i.e., a customer would have to purposefully change the region)[2].

Third, treatment and control regions need to follow a common trend (Lechner 2010): if the treated regions had not been subjected to the treatment (here, the store opening), they should have experienced the same time trends as the control regions. Put differently, it requires that in the absence of treatment, the difference in the outcome variable of interest between the treatment and control regions is constant over time. Drivers of such a diverging trend could be demographic and shopping behavior characteristics – for instance, as one region develops economically more quickly than the rest. If we consider the common trend assumption contingent on these drivers, matching on them prior to the store opening should reduce the risk of violating this assumption. In line with extant research (Avery et al. 2012b), we therefore used matching of the regions (vs. controlling with sociodemographics; van Nierop et al. 2011) to ensure the treatment and control groups followed a common trend.

Matching has become an increasingly popular method in many research fields, including marketing (Garnefeld et al. 2013; Eggert, Steinhoff, and Witte 2019). The basic idea is that in observational studies, variables that affect the outcome variable may be distributed differently across treatment groups, thereby confounding the treatment effect (Cochran and Rubin 1973). The goal of matching is to eliminate or reduce the effect of exogenous variables that affect the modelling outcome, so that subsequent statistical methods applied to the

[2] The subsequent matching excluded zip codes proximal to the store opening, thereby preventing any self-selection through travelling. In the matched treatment zip codes, only .6% of all purchases arose from store sales, indicative of a change of regions.

matched subset have reduced model dependence, estimation error, and bias (Ho et al. 2007; Rubin 1974).

Aggregation. We matched data on a regional level (i.e., zip codes), similar to extant research (Avery et al. 2012b). We did not investigate changed behavior on a transaction level (Huang, Lu, and Ba 2016), because an aggregation also includes new customers that were acquired during the period of the store introduction, whereas an individual-level comparison would only differentiate between those existing customers that adopted the new channel (here, the brick-and-mortar store; this accounts for .1% of the total customers) and those who did not (19.9% of total customers; as in, e.g., Pauwels and Neslin 2015), which would exclude new customers acquired after the store opening, reduce the sample size, and cause a self-selection bias. Therefore, for each week, we aggregate our data by zip code. Although doing so reduces the size of the calculation sample, the data set is still based on all purchases. After aggregation, our data set consisted of sales data for 10,152 zip code regions (before store opening). We then selected the treatment regions using a 10-kilometer circumference around the store opening[3], which resulted in 114 zip codes as treatment regions.

Matching. For each of these treatment regions, we selected five regions that were most comparable. We used a set of demographic and shopping behavior variables to match the data (Avery et al. 2012b): cumulated gross sales per customer, cumulated operating profit per customer, operating margin, number of orders, share of new customers, share of returns, and share of sensory products. Moreover, because the store was opened in a city, we created an urbanization dummy for each zip code region (i.e., located in a city with population >100.000) as additional matching criterion.

[3] We set a 10-kilometer radius around the store as a maximum distance a consumer would be willing to travel to visit a store within a metropolitan region (VuMa (2018). We also tested the robustness of our findings with an alternative definition of the treatment region (i.e., 5 kilometers; see Appendix A), but the results did not change substantially.

	Before matching						After matching					
Variable	**MT**	**MC**	**Mdiff**	**p**	**KS-Stat**	**KS-BS**	**MT**	**MC**	**Mdiff.**	**p**	**KS-Stat**	**KS-BS**
Gross sales per customer	894.43	1,016.80	–122.37	.12	.22	.00	894.43	885.08	9.35	.44	.09	.02
Operating profit per Customer	41.20	73.69	**–32.49**	.00	.30	.00	41.20	41.48	–.28	.91	.07	.10
Operating margin	n/a[a]	n/a[a]	.00	.80	.31	.00	± .00[b]	.00[b]	–.00	.85	.05	.47
Share returns	n/a[a]	n/a[a]	**.03**	.00	.26	.00	± .00[b]	–.03[b]	–.00	.51	.09	.01
Share sensory products	n/a[a]	n/a[a]	**–.02**	.00	.40	.00	± .00[b]	.02[b]	–.00	.66	.09	.01
Share new customers	n/a[a]	n/a[a]	**–.05**	.00	.28	.00	± .00[b]	–.05[b]	–.00	.90	.09	.02

Note: Boldfaced values are significant on a 5% level; MT = mean treatment, MC = mean control, Mdiff = mean difference, *p* = T-test *p*-value, KS-Stat = KS-statistic, KS-BS = KS bootstrap *p*-value, Footnotes: [a]Data not reported upon request of the retailer; [b]Differences before and after matching/

Table 4 (B): Summary statistics and covariate comparison before and after matching

We used a 1-to-n (here, n = 5) matching without replacement, in which we selected five matching zip code regions for each treatment zip code (Sekhon 2011), which we averaged after selection to further mitigate any potential region-specific unobserved trends. Note that because we use an average control region, the sample size remained constant (1-to-5 vs. 1-to-1 region). All results remain consistent also when using a 1-to-1 matching (see Appendix B). Although the common trend assumption is not formally testable, because it relies on counterfactual outcomes (Callaway and Sant'Anna 2018), we use the commonly applied procedure of visual inspection to support this assumption (Wing, Simon, and Bello-Gomez 2018; see Fig. 2). Table 4 shows summary statistics before and after matching. Note that before matching, the treatment regions differed from all other regions on four of six indicators ($p < .05$), but after the matching, none of the indicators differed significantly. Table 5 provides the correlation of performance variables; both tables use data on a zip code level.

Variable	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**
Gross sales per customer	1,310.06	(14,246.55)	1					
Operating profit per customer	104.98	(642.67)	**.92**	1				
Share new customers	.56	(.26)	**−.02**	**.06**	1			
Share returns	.32	(.23)	.01	**−.13**	**−.37**	1		
Share sensory products	.73	(.27)	−.01	**.05**	**.07**	**.43**	**1**	
Share offline sales	.01	.05	.00	**.02**	**.05**	**−.04**	**.05**	**1**

Note: Boldfaced values are significant on a 5% level.

Table 5 (B): Correlation of performance variables on zip code level

For each pair of matched regions and time period, we calculated the difference between the treatment and the matched control regions. For instance, for the difference in gross sales, we calculated the following:

$$[1] \qquad gross.sales_t = gross.sales.treatment_t - average.gross.sales.controls_t$$

Model. Our main goal is to understand the overall effect of the store opening on the firm's sales and profitability. To this end, we specified the following regression models (note that all regression are estimated independently, not as equation system, and we only write them in matrix notation for brevity):

$$[2a] \qquad \mathbf{y}_{\mathrm{it}} = \boldsymbol{\beta}_\mathbf{0} + \mathbf{A}^\mathbf{T}\,\mathbf{x}_\mathbf{t} + \mathbf{B}^\mathbf{T}\,\mathbf{z}_\mathbf{it} + \boldsymbol{\Gamma}^\mathbf{T}\,\mathbf{v}_\mathbf{it} + \boldsymbol{\alpha}_\mathbf{i} + \boldsymbol{\varepsilon}_\mathbf{it}$$

$$[2b] \qquad \begin{bmatrix} gross.sales_{it} \\ operating.margin_{it} \\ operating.profit_{it} \end{bmatrix} = \boldsymbol{\beta}_\mathbf{0} + \mathbf{A}^\mathrm{T} \begin{bmatrix} step.dummy_t \\ pulse.dummy_t \\ post.open.weeks_t \end{bmatrix} + \mathbf{B}^\mathrm{T} \begin{bmatrix} share.offline.sales_{it} \\ share.returns_{it} \\ share.sensory.products_{it} \\ share.new.customers_{it} \end{bmatrix} + \boldsymbol{\Gamma}^\mathrm{T} \begin{bmatrix} rainfall_{it} \\ sun.hours_{it} \\ holiday.dummy_{it} \end{bmatrix} + \boldsymbol{\alpha}_\mathbf{i} + \boldsymbol{\varepsilon}_\mathbf{it}$$

The right-hand side of Eq. 2 comprises the effects (matrices of model-specific regression coefficients) of three sets of variables: (1) variables concerning the store opening ($\mathbf{A}^\mathbf{T}$: 3 × 3 matrix), (2) explanatory variables ($\mathbf{B}^\mathbf{T}$: 3 × 4 matrix), and (3) control variables ($\boldsymbol{\Gamma}^\mathbf{T}$: 3 × 3 matrix).

Three variables $\mathbf{x}_\mathbf{t}$ measure the short- and long-term effects of the store opening (H5). In line with extant research (Deleersnyder et al. 2002; Avery et al. 2012b), we included a step dummy, a pulse dummy, and a count of the weeks after the store opening. First, the *step.dummy$_t$* variable represents the store opening intervention, taking the value 0 before the store opening and 1 afterward. The sign of its coefficient indicates whether opening a store has a positive or negative impact on the outcome variable that persists over time. Second, the variable *pulse.dummy$_t$* is a dummy variable that takes the value 0 except for the two weeks after the store opening to capture any short-term reactions to the store opening. Third, *post.open.weeks$_t$* represents the number of weeks since the store opening, taking values between 0 (before the store opening) to 51 (according to the week after the store opens). Its coefficient indicates whether the store opening is increasingly beneficial (if sign is positive) or detrimental (if sign is negative) to the outcome variables of interest.

In line with our theorizing, we included a set of explanatory variables $\mathbf{z_{it}}$: *share.offline.sales*$_{it}$, *share.returns*$_{it}$, *share.sensory.products*$_{it}$, and *share.new.customers*$_{it}$. They measure the difference between the treatment region *i* and its matched control regions at time *t* with respect to (1) share of sales generated through the offline channel (vs. online channel; H1b), (2) share of sales generated by products that were returned (vs. products that were not returned; H2b), (3) share of sales generated by sensory products (vs. nonsensory products; H3b), and (4) share of new (vs. existing) customers (H4b). Our analysis also assesses whether these four variables were affected by the store opening (H1a, H2a, H3a, and H4a).

Finally, we added a set of control variables $\mathbf{v_{it}}$ to capture potential region-specific effects that may have affected our results. Specifically, because the weather differs by region and could substantially influence sales in a given period (Moon et al. 2018), we included a measure of the weekly volume of rainfall (*rainfall*$_{it}$) and the weekly hours of sun for a given zip code (*sun.hours*$_{it}$) – again measured as the difference between treatment and its matched control regions. Furthermore, we controlled for public holidays during which stores are closed (*holiday.dummy*$_{it}$), which might also have differed between regions and thus affected sales. Note that all effects remain consistent without these controls.

Utilizing the panel structure of our data (i.e., 114 pairs of treatment and control regions over 103 weeks), we employed a Least Squares Dummy Variables (LSDV) estimator for fixed effects (McCaffrey et al. 2012) to account for potentially unobserved time-invariant effects of the individual treatment regions (α_i) (Wooldridge 2012); for relative measures (e.g., operating margin), we used a weighted regression because we are interested in the effects of the variables on the company as a whole; small (and, thus, economically irrelevant) regions might otherwise strongly influence the overall result[4]. To test for robustness, we also used pooled ordinary least squares regression, in line with previous studies in this field (e.g., Avery et al. 2012b). Our results were robust to these alternative model specifications (see Appendix C for results).

[4] For example., the average of weekly difference in share of returns of one treatment region differed by 85% from the respective average for all treatment regions, even though the region only generated .32% of weekly revenues, on average.

5.2 Segment-specific Effect: Latent Class

In addition to the overall effect of the store opening, we are interested in understanding potentially unobserved heterogeneity among different segments of existing customers (H6). Although this substantially reduced our data set to those customers that purchased before and after the store introduction in the target region (114 zip codes), this knowledge is invaluable for retailers to understand segment-specific channel usage to optimize their channel system (Inman, Shankar, and Ferraro 2004). This restriction to existing customers with pre- and post-introduction purchases resulted in a data set of 40,418 orders (~ 1.6 % of all orders) from 9,575 customers (~ 0.8 % of all customers). For these customers, we estimated an individual-level data finite mixture model (FMM), commonly referred to as latent class regression. The logic behind this approach is that we empirically capture response heterogeneity without having to formulate a priori hypotheses (McLachlan and Peel 2004). Because of their flexibility, FMMs have been applied increasingly in various fields to classify observations and to model unobserved heterogeneity (e.g., Pauwels et al. 2011b; Wedel and DeSarbo 1993; Konuş, Verhoef, and Neslin 2008b).

Because we are interested in the effect of the store opening on different customer segments' profitability, we use the operating profit as a dependent variable and explain it with the three store introduction variables (step, pulse, and count) introduced previously in the quasi-experimental design (see Eq. 2b). We use the operating profit, and not the profit margin, because it is a frequent decision criteria for choices of a store location. Managers who consider store openings are primarily interested in regions with high share of customers showing exceptionally strong positive effects in terms of absolute profit, as it is used to cover investments associated with store openings (e.g., rent, staff). Methodologically, individual-lvel profit margin models would result in strongly unbalanced panels, as profit margins could only be computed for periods with a purchase – and the frequency of these varies strongly between customers.

We include a distance measure for the individual customer from the store ($store.distance_{it}$; see also Pauwels and Neslin 2015b) and a Christmas season dummy ($christmas.dummy_t$), which captures the strongest seasonal effect. This results in Eq. 3:

[3] $$\begin{aligned}\text{operating.profit}_{it} &= \beta_0 + \beta_1\ \text{step.dummy}_t + \beta_2\ \text{pulse.dummy}_t \\ &+ \beta_3\ \text{post.open.weeks}_t + \beta_4\ \text{store.distance}_{it} \\ &+ \beta_5\ \text{christmas.dummy}_t + \varepsilon_{it}\end{aligned}$$

The parameters β in the statistical model may differ across latent classes; that is, we allow the model to segment customers based on all their individual regression coefficients.

6 Empirical Results

6.1 Overall Effect

Model-free evidence: Fig. 2 displays the development of the differences in the analysis variable before and after the store opening. Gross sales and profit increase after the introduction, but the descriptive result is inconclusive for the operating profit margin (initial increase, followed by a decline and then a positive long-term trend). Sales-related costs increase after the opening of the store. The share of returns decreases after the store opening but increases over time. The share of sensory products shows an initial increase shortly after the store introduction but then a decrease in the weeks after the opening. However, over time the data show a steady increase in the share of sensory products. Moreover, the share of new customers increases after the store introduction and shows a positive long-term trend.

Models: We first assessed the overall effect of the store opening on the firm's sales and profitability. In line with extant research, we find gross sales to be positively affected by the store opening (Table 6, Model 1a: $\beta_{step.dummy} = 1{,}107.44$, $p < .001$). In addition, the store opening increased the retailer's absolute operating profit (Model 1b: $\beta_{step.dummy} = 159.62$, $p < .001$). Interestingly, however, we do find mixed support for H5, in that the store opening is also associated with a deterioration of the operating profit margin (Model 1c: $\beta_{step.dummy} = -.019$, $p < .01$), although this effect improves over time ($\beta_{post.open.weeks} = .001$, $p < .001$). A bootstrapped (n = 5,000; Hayes 2018b) assessment of the total effects (i.e., sum of store opening–related variables; see matrix A^T) over time underscores this finding (see Fig. 3: while revenue and absolute operating profit increase directly after the store opening, the operating profit margin needs 24 weeks to reach pre-opening levels).

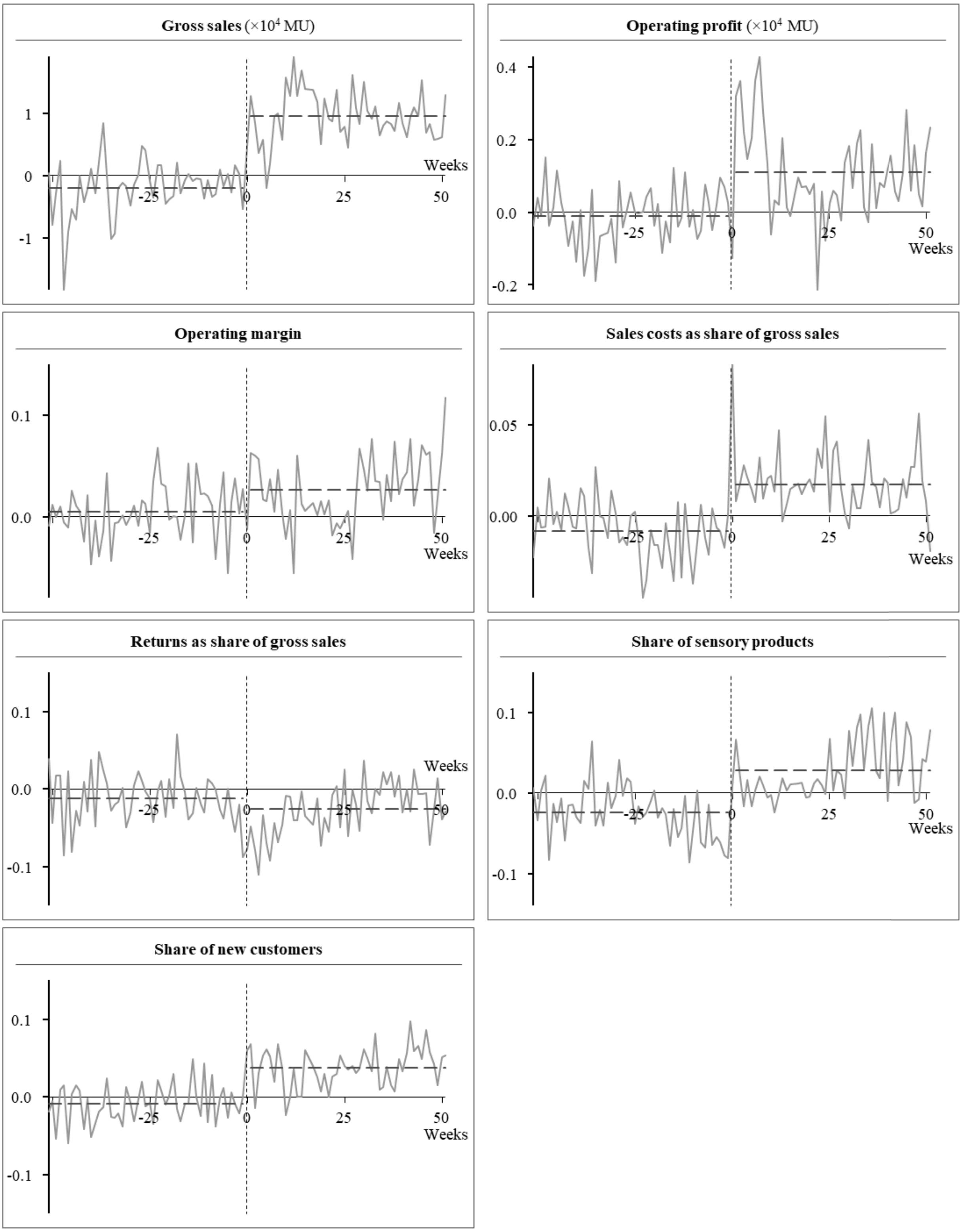

Fig. 2 (B): Mean values of differences between treatment and matching regions

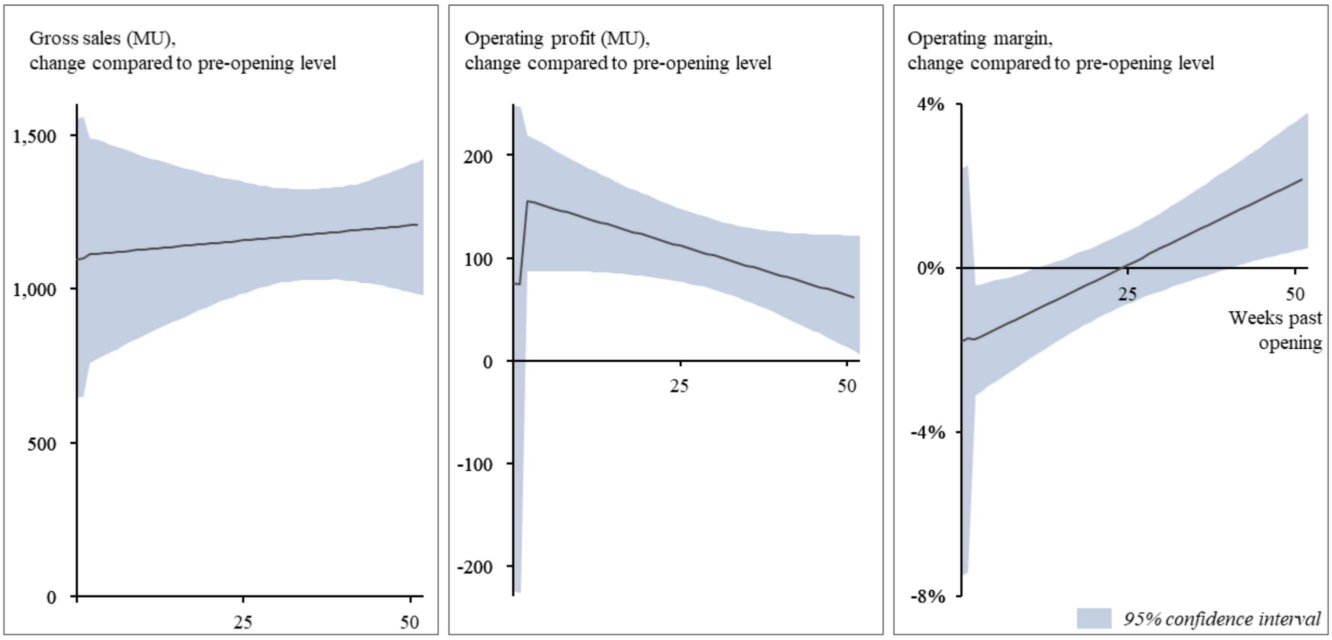

Fig. 3 (B): Bootstrapped total indirect effects of the store introduction on dependent variables

Note that the declining absolute trend for operating profits is due to the modelling with a time trend for the weeks after the opening[5]. We, therefore, see mixed evidence for profitability: although profits increase absolutely, we find a negative short-term effect of a store opening on the operating margin.

To assess the drivers of the profitability effect, we regress the mediators of our conceptual model (channel mix and associated sales-related costs [proxied by the share of offline sales]; return rate; product mix [share of sensory products]; and customer mix [share of new customers]) on the store opening dummies (models 2a–2d). In support of H1a, the store opening increases the share of offline sales (Model 2a: $\beta_{step.dummy} = .122$, $p < .001$; $\beta_{pulse.dummy} = .071$, $p < .001$). We also find support for H2a, in that the store opening leads to a reduction in the share of returned products (Model 2b: $\beta_{step.dummy} = -.069$, $p < .001$). This effect, however, vanishes over time ($\beta_{post.open.weeks} = .001$, $p < .001$). The effect of the store opening on the share of sensory products is less straightforward: A negative overall effect (Model 2c: $\beta_{step.dummy} = -.020$, $p < .01$) is overshadowed by a positive short-term effect ($\beta_{pulse.dummy} = .076$, $p < .001$) and a positive time trend ($\beta_{post.open.weeks} = .002$, $p < .001$). Thus, the store

[5] An alternative model specification without the time trend variables shows a positive step ($\beta = 109.39$, $p < .001$) and a nonsignificant pulse dummy ($\beta = -29.65$, $p > .10$).

opening, apart from a short period from weeks 2 to 10 after the initial opening, has a positive effect on the share of sensory products, which is consistent with Fig. 2 and H3a. Also consistent with Figure 2 and the corresponding hypothesis (H4a), we find the store opening to increase the share of new customers, especially over time (Model 2d: $\beta_{pulse.dummy} = .045$, $p < .01$; $\beta_{post.open.weeks} = .001$, $p < .001$).

As hypothesized, these drivers also influence the profit margin. In support of H1b, we find the share of offline sales to be negatively associated with the retailer's operating profit and operating profit margin (Model 3b: $\beta = -308.21$, $p < .001$; Model 3c: $\beta = -.111$, $p < .001$). This negative profit margin effect results from the higher sales-related costs of the offline compared with the online channel (48% vs. 23% of total costs), although the latter decline over time. As anticipated, the share of returned products negatively influences the retailer's operating profit and operating margin (Model 3b: $\beta = -1{,}466.96$, $p < .001$; Model 3c: $\beta = -.477$, $p < .001$), in support of H2b. We also find support for H3b, in that the share of sensory products increases the retailer's operating profit and operating margin (Model 3b: $\beta = 1{,}216.74$, $p < .001$; Model 3c: $\beta = .506$, $p < .001$). In support of H4b, the share of new customers positively influences the retailer's operating profit and operating margin (Model 3b: $\beta = 120.73$, $p < .001$; Model 3c: $\beta = .055$, $p < .001$).

If we assess the standardized coefficients to compare the effect sizes, we find that the reduction in the share of returns and the increase in sensory products have an equal influence on the absolute operating profit (see Appendix D, Table 1, Model 3b: $\beta_{returns} = -.393$ vs. $\beta_{sensory} = .397$), while the share of offline sales and the share of new customers exert a much smaller influence ($\beta_{offline.share} = -.056$, $\beta_{new\ customers} = .029$). The same holds for the effects on the operating profit margin (Model 3c: $\beta_{returns} = -.578$ vs. $\beta_{sensory} = .576$, $\beta_{offline.share} = -.127$, $\beta_{new\ customers} = .050$).

		Gross Sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	1,107.44 ***	159.62 ***	–.02 **	.12 ***	–.07 ***	–.02 **	.00	769.05 ***	97.49 ***	–.03 ***
		(144.06)	(30.56)	(.01)	(.01)	(.01)	(.01)	(.00)	(134.93)	(27.85)	(.01)
	Pulse Dummy (+ 2 weeks)	–11.80	–83.89	.00	.07 ***	.04 *	.08 ***	.05 **	–505.90	–129.90 *	–.01
		(334.51)	(70.95)	(.02)	(.01)	(.02)	(.02)	(.02)	(309.45)	(63.86)	(.01)
	Post Open Week Dummy	1.97	–1.91 *	.00 ***	.00 ***	.00 ***	.00 ***	.00 ***	–19.37 ***	–1.12	.00 ***
		(4.43)	(.94)	(.00)	(.00)	(.00)	(.00)	(.00)	(4.14)	(.86)	(.00)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	5,287.00 ***	–308.21 ***	–.11 ***
									(254.04)	(52.43)	(.01)
	Share Returns	—	—	—	—	—	—	—	3,215.37 ***	–1,466.96 ***	–.48 ***
									(170.62)	(35.21)	(.01)
	Share of Sensory Products	—	—	—	—	—	—	—	2,354.85 ***	1,216.74 ***	.51 ***
									(149.49)	(30.85)	(.01)
	Share of New Customers	—	—	—	—	—	—	—	599.37 ***	120.73 ***	.06 ***
									(177,52)	(36.64)	(.01)
Controls	Holiday Dummy	–63.46	–77.68 **	–.02 ***	–.00	.03 ***	–.01	–.00	–124.70	–45.74 †	–.01
		(124.61)	(26.43)	(.01)	(.00)	(.01)	(.01)	(.00)	(115.17)	(23.77)	(.01)
	Sun Hours	3.06	–1.89 **	–.00 ***	–.00 ***	.00 ***	.00 †	–.00 ***	1.90	–1.92 **	–.00 ***
		(3.30)	(.70)	(.00)	(.00)	(.00)	(.00)	(.00)	(3.05)	(.63)	(.00)
	Rainfall	–10.67 *	–3.55 **	–.00 **	.00	.00 †	.00	–.00	–11.59 *	–3.43 ***	–.00 **
		(5.11)	(1.08)	(.00)	(.00)	(.00)	(.00)	(.00)	(4.72)	(.97)	(.00)
Constant		–221.13 **	–34.21 *	.08 ***	.03 ***	.04 ***	.11 ***	.12 ***	–94.61	43.22 **	.05 ***
		(81.74)	(17.34)	(.00)	(.00)	(.00)	(.00)	(.00)	(75.64)	(15.61)	(.00)
R^2		.37	.13	.06	.61	.07	.05	.12	.46	.30	.41
N		11,418	11,418	11,071	11,071	11,071	11,071	8,898	11,414	11,414	11,067
dfres		226,870.50	191,093.40	–3,263.50	–10,071.20	918.60	–253.70	–5,168.4	225,076.20	188,667.10	–8,455.40

Note: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .00$

Table 6 (B): Unstandardized regression coefficients for difference models

To further assess the practical relevance of the mediators, we conducted a bootstrapped analysis of the mediation paths (n = 5,000), that is, the indirect effects of the store opening on the three dependent variables through the four mediators at three points in time (i.e., 2, 25, and 51 weeks after the store opening[6]; see Appendix E). We find all indirect effects on profit margin to be significant for weeks 2 and 25 after the store opening. Only after a longer period do the indirect effects of the store opening through share of returns become insignificant. However, the remaining main effects in Models 3a–3c indicate a partial mediation (i.e., both a complementary and a competitive mediation, depending on the referred mediator), which means that the mediators identified are consistent with our hypothesized theoretical framework but probably not exhaustive (Zhao, Lynch, and Chen 2010).

6.2 Segment-specific Effect

Table 7 shows the results for the effects of the store, based on a latent class regression analysis (LCA) with the absolute operating profit as the dependent variable. We chose the latent class model with three different segments, in line with three segment solutions of previous works on the effect of channel extensions (Pauwels et al. 2011b; Konuş, Verhoef, and Neslin 2008b). Technically, the five-segment solution shows a slightly lower Akaike information criterion, but interpreting a solution with so many subgroups would be managerially difficult. We therefore draw rather on interpretability and managerial relevance as criteria for selecting the number of segments, a common approach in marketing (e.g., Lehmann, Gupta, and Steckel 1998; Rust, Lemon, and Zeithaml 2004).

[6] We did not choose the week of the store opening or the week after to exclude the short-term effect (impulse dummy).

Operating Profit	All Customers		Segment 1		Segment 2		Segment 3	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Step Dummy	1.06 ***	(.15)	.84 ***	(.13)	.31 ***	(.04)	3.21 ***	(.75)
Post Open Week	–.03 ***	(.00)	–.02 ***	(.00)	–.01 ***	(.00)	–.10 ***	(.02)
Impuls (+2 Weeks)	.11	(.35)	–.14	(.31)	–.19 *	(.10)	1.36	(1.73
Distance dummy1 (≤3km)	.01	(.31)	–.18	(.28)	–.11	(.09)	.12	(1.56
Distance dummy2 (≤5km)	–.32	(.31)	–.25	(.28)	–.15	(.09)	–.58	(1.56
Distance dummy3 (≤10km)	–.30	(.31)	–.48	(.27)	–.21 *	(.09)	.00	(1.53
Christmas dummy	–.23	(.19)	–.57	(.17)	–.31 ***	(.05)	.74	(.97)
Segment Size	100.0%		41.6%		40.1%		18.3%	

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

Table 7 (B): Regression coefficients and standard deviation for LCA

To compare the different segments, we conducted a one-way analysis of variance of key variables for the period prior to the store introduction. Table 8 reports the average values per customers before the store opening and compares the segments. The results of the LCA indicate that the profitability effect of the store opening is most positive for segment 3, although this effect diminishes over time (see Table 7: $\beta_{step.dummy} = 3.21$, $p < .001$; $\beta_{post.open\text{-}week} = -.10$, $p < .001$). This segment comprises, on average, high-volume customers that show the highest values for gross sales (1,981 MUs) and operating profit (187 MUs). These customers spend a higher share on sensory products (on average, 71%) and return more (22% of gross sales). At the same time, these customers show a higher operating margin than the other segments (+9%). We interpret these customers as the small share of power shoppers (18.3% of customers) who are eager to try the new store, which results in a positive profit margin effect. However, this effect does not last long, as the negative time dummy in the LCA shows. This finding supports H6.

Variable	Total		Segment 1		Segment 2		Segment 3		F	p-value
	Mean	SD	Mean	SD	Mean	SD	Mean	SD		
Avg. gross sales	995.40	(1,542.83)	997.45	(1,065.21)	543.76	(450.64)	1,981.37	(2,926.87)	586.67	.00
Avg. operating profit	19.13	(331.74)	–16.35	(220.42)	–20.73	(69.00)	187.02	(667.92)	291.69	.00
Resulting operating margin	2%		–2%		–4%		9%		n/a	
Avg. share of returns	.11	(.28)	.17	(.33)	.01	(.11)	.22	(.35)	476.23	.00
Avg. share of sensory products	.28	(.44)	.35	(.46)	.05	(.21)	.71	(.42)	1,879.65	.00
Avg. share of offline sales	.00	(.00)	.00	(.00)	.00	(.00)	.00	(.00)	–	–
Segment share	100.0%		41.6%		40.1%		18.3%			

Table 8 (B): Average values (on customer basis) per segment for period before store opening

Segment 1 seems to represent the average customer in terms of total spending, return rate, and share of sensory products, although the operating margin is below the average. According to the LCA, these customers are not affected by the store opening. Segment 2, in contrast, showed only limited spending and low profitability before the store opening, but their profit margin increases thereafter. Possibly, those customers were hesitant to use the online pure-play model extensively, but were happy to use the new brick-and-mortar channel.

7 Discussion of the Results, Implications, and Future Research

7.1 Summary

This research offers the first indication of the profitability effect of adding bricks to clicks, that is, a .physical store opening in addition to an online shop. One year after the store opening, we find that a store opening increased not only revenue in the store region (relative step effect: +27.0%), but also operating profits (relative step effect: +48.3%; i.e., after costs of goods sold and sales-related costs, such as logistics and store costs, were subtracted). The *profit margin* effect is positive after one year (+2.2%), but the profit margin declines directly after the store opening (relative step effect: −1.8%) and does not reach pre-opening levels until about 24 weeks after the opening.

We establish four drivers of this effect: changes in (1) sales-related costs, (2) return rates, and (3) the product mix, that is, the share of sensory products; and (4) the acquisition of new customers. Sales-related costs (1) increase immediately after the opening of a store, as the high fixed costs of a store (i.e., staff and rent) must be borne by a low number of transactions. This negatively effects the profit margin. However, this negative effect is mitigated over time, as the revenue of the store increases. Keeping the other profitability drivers constant, we estimate that about 157 orders per day would constitute a level at which the brick-and-mortar store reaches levels of sales-related costs equal to the online store's. This finding has high face validity, as it matches managerial discussions on the assimilation of on- and offline sales-related costs ("CAC [i.e., customer acquisition costs] is the new rent"; e.g., Siddiqi 2018; Hensel 2019).

The remaining three profitability drivers improve profitability directly after the opening of a store. Return rates (2) drop in the region where the store opened, likely driven by not only the customers' ability to try the product before purchasing, but also a higher share of physical store sales (where return rates are much lower than online). Further, customers purchase more sensory products (3), that is, products that benefit from experiential tests before purchase, which increases the profit margin. Finally, the store opening attracts (4) new customers, which not only generate additional revenue but also improve the profit margin.

Finally, we find that the profit effect of a store opening differs by segment of existing customers: it has the strongest positive effect for customers who used the retailer's offering and were highly profitable prior to the store opening. We interpret this finding as consequence of either their high involvement and/or the fact that they were simply better informed (or more ready to recognize information) about the store opening. In line with this interpretation, the positive profitability effect for this segment declines over time – possibly as they satisfy their initial interest. The profitability effect for the remaining two segments is much smaller: a medium positive effect arose for a group of small-basket and unprofitable shoppers – possibly because they were hesitant to order from the online store (segment 2). In contrast, the largest segment (1), which was also very comparable to the average customer, was hardly affected by the store opening. Therefore, we conclude that part of the positive store opening effect results from bringing hesitant and highly involved customers to the store. In addition, newly acquired customers – a notable share of the orders after the store opening (37% of store orders) – must also show positive order characteristics, as the overall effect of the opening is lastingly positive.

7.2 Managerial Implications

Our findings yield various insights for channel expansions, especially from the perspective of online pure players. Managers can assume that adding offline channels to an online channel system is favorable in terms of absolute operating profits as well as – after an initial decline –for the operating profit margin. However, to make optimal use of this profit effect, retailers must be aware of the associated profit levers: the change in return rates has the strongest effect on the profit margin ($e = -.31$; at mean values of independent variables; please note that the overall effect of the mediation through return rate is positive, as the latter decreases after the store opening), followed by the change in the channel mix towards the offline channel ($e = -.29$, which turns positive over time). The product mix, that is, the share of sensory products ($e = .03$), and the share of new customers ($e = .03$) also show a positive profit margin effect.

First, profitability might be increased by increasing the sale of sensory products in new brick-and-mortar stores. Store concept elements should take this into consideration and be designed to utilize customers' ability to touch and test products within the store physically and encourage them to do so (with, e.g., store ambience, furniture selection, staff recommendations). In this vein, sensory elements (e.g., haptics, visual support, taste samples; Krishna 2012) might strengthen consumers' inclination to engage with the products. Furthermore, sensory products should be presented prominently on special furniture and shelves that invite customers to engage in such physical interaction. This recommendation might be generalized to any product category that offers attractive profit margin, as the store might be used to feature these products more prominently.

Second, as product returns around the store decline, because a share of the consumers can physically interact with the products in their omnichannel journey and gains more confidence in what to order, retailers might aim to get online-only shoppers at a certain stage of their purchase process in the store. Specifically, retailers might incentivize store visits for customers who have returned products after their first online orders (Melis et al. 2016). In addition, retailers could encourage customers to visit the store for products with high return rates (e.g., by offering online store visitors an incentive to visit a specific product site and try the product in the store). The usage of cross-channel services such as click-and-collect could also be favorable for shifting online customers to new offline stores.

Third, retailers could support the acquisition of new customers through their store. Although a store opening creates a positive effect on the share of new customers in a region and, in turn, on the profit margin, this effect might be further strengthened (e.g., through billboard advertising in the region around the store).

Finally, retailers should be aware of the development of sales-related costs over time. High fixed costs can render stores unprofitable in the first months after the opening. As the high initial sales-related costs of a store can be lowered through utilization, retailers should aim to increase the number of visitors. To this end, our results suggest that heavy online users prior to the store opening will be most eager to try the new store. Thus, a customer relationship campaign targeted at attracting this customer segment to the store (e.g., through inviting them to an opening party) might help bridge an initial gap in the store's profit margin.

7.3 Theoretical Implications

This research theoretically contributes in three dimensions. First, we show that the channel complementarity suggested in the omnichannel paradigm extends to not only revenues but also profit margins, answering multiple explicit calls for research (Pauwels and Neslin 2015b; Avery et al. 2012b; Verhoef, Kannan, and Inman 2015b).

Second, we establish four drivers that influence the profit margin effects of channel additions (channel mix and associated channel sales-related costs, return rate, and product and customer mix). In doing so, we extend drivers of omnichannel interaction beyond overall effects (e.g., the stores acting as billboard: Wang and Goldfarb 2017), highlighting that channel-specific capabilities can drive complementarity in an omnichannel system. Although the four drivers comprehensively assess the most managerially relevant drivers of channel profitability, we theoretically find that they only constitute a partial (complementary and competitive) mediation; this result indicates that omitted mediators are likely (Zhao, Lynch, and Chen 2010), which points to the necessity for future research to investigate additional mediators.

This finding leads to our third theoretical implication: that the effects of channel additions might vary over time. Whereas extant research has only established a time-independent effect of channel additions as evidenced by changes in individual behavior (e.g., less loyalty, more price comparison; Ansari, Mela, and Neslin 2008), we suggest that time-dependent profitability effects are strongly related to a decrease of the fixed costs of a store opening spread over a growing offline customer base. Finally, we find evidence for a segment-specific effect of channel additions with respect to profitability, similar to the segment-specific revenue effect of channel additions (Pauwels et al. 2011b).

7.4 Limitations and Future Research

Our research is limited in three domains. First, although this research is the first to establish a profitability effect of store additions, we only determine the effect on operating profit and profit margin. Our profitability research goes beyond the gross profit level commonly reported by retailers, which considers only the cost of goods sold, to also include sales-related costs; however, we do not test the effect on the retailer's EBIT margin, which would also account for overhead costs. Using this measure might affect profitability; for instance, generating additional revenue from a store opening might help decrease fixed overhead costs. However, adding the complexity of another channel might require additional staff with different capabilities, which would again increase the overhead costs. In addition, we only assess the effect for the region of the store and not for retailers as a whole.

Second, we investigated effects from opening one brick-and-mortar store only, although we do use a large set of treatment regions around this store (and matched control regions). We are confident as to the representativeness of the store opening and the robustness of our findings, as we employed extensive matching and the retailer's management team assured us that the store characteristics, its regional setting, and the effects of its opening were representative for the now extended set of stores. That said, future research could explore how results might differ depending on characteristics of the store openings. We test the effect comparing regions with matched characteristics, but store performance might vary depending on where the store is located (Reinartz and Kumar 1999). Specifically, the effects of store openings have to date not been investigated with respect to the characteristics of the surrounding region (e.g., metropolitan vs. urban vs. rural area). Further, the opening sequence might matter; for instance, highly involved customers might accept a longer drive for the first store opening, but not for later ones. Furthermore, it would be interesting to investigate whether adding an online store to a brick-and-mortar sales network has a reverse (i.e., negative) profitability effect to adding bricks to clicks (similar to the revenue effect investigated in Biyalogorsky and Naik 2003; van Nierop et al. 2011; or the channel elimination in Konuş, Neslin, and Verhoef 2014).

Finally, the employed difference-in-differences modelling approach offers many advantages but is also subject to some limitations that result from the necessary specifications. First, the quasi-experimental approach with difference-in-differences controls for unobserved variables, such as competitive action. However, the matching necessary for the quasi-experimental analysis relies on selecting matching criteria, which renders the result sensitive to the conditioning variables (Heckman and Navarro-Lozano 2004). Moreover, during the period of analysis the management team assured us that they did not take actions endogenous to the store opening (e.g., opening of another store, changes in prices for stores only, specific regional marketing campaigns). Further, our research specifies the catchment area of the store for which we analyze the opening effect (10-kilometer radius for treatment region vs. a measure based on travel time; Avery et al. 2012b). Although we test alternative specifications in robustness checks, our analysis only retrospectively assesses the effect for a certain catchment area. A reverse analysis might be worthwhile for retailers: understanding which catchment area would be required for a profitable store opening could help them in their location screening. Finally, although our results remain robust with alternative specifications (e.g., different matching variables, matching ratio), it would be fruitful for future research to test whether model specifications determine the estimated effect of channel additions.

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9 Appendix

		Gross Sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Cus-tomers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	3,619.37 ***	314.42 ***	–.00	.17 ***	–.09 ***	–.01	.01	2,407.09 ***	315.21 ***	–.02 †
		(352.80)	(68.85)	(.01)	(.01)	(.01)	(.01)	(.01)	(334.73)	(65.55)	(.01)
	Pulse Dummy (+ 2 weeks)	–1,343.19	–447.79 **	–.04 †	.08 ***	.06 *	.07 *	.04 †	–2,569.71 ***	–405.75 **	–.04 *
		(820.00)	(160.03)	(.02)	(.02)	(.03)	(.03)	(.02)	(759.45)	(148.72)	(.02)
	Post Open Week Dummy	–35.42 **	–5.67 **	.00	.00 ***	.00 ***	.00 ***	.00 ***	–86.06 ***	–3.29 †	.00 *
		(10.81)	(2.11)	(.00)	(.00)	(.00)	(.00)	(.00)	(10.20)	(2.00)	(.00)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	11,519.65 ***	–1,041.83 ***	–.16 ***
									(628.11)	(123.00)	(.02)
	Share Returns	—	—	—	—	—	—	—	3,565.56 ***	–1,883.19 ***	–.46 ***
									(469.71)	(91.98)	(.01)
	Share of Sensory Products	—	—	—	—	—	—	—	3,243.53 ***	1,586.63 ***	.48 ***
									(424.43)	(83.12)	(.01)
	Share of New Customers	—	—	—	—	—	—	—	411.16	279.94 **	.08 ***
									(529.24)	(103.64)	(.02)
Controls	Holiday Dummy	–284.08	–136.26 *	–.03 ***	.00	.04 ***	–.01	–.00	–523.73 †	–81.32	–.01
		(306.19)	(59.76)	(.01)	(.00)	(.01)	(.01)	(.00)	(283.07)	(55.43)	(.01)
	Sun Hours	15.93 †	–1.92	–.00 **	–.00 **	.00 *	.00	–.00	18.46 *	–2.92 †	–.00 **
		(8.76)	(1.71)	(.00)	(.00)	(.00)	(.00)	(.00)	(8.11)	(1.59)	(.00)
	Rainfall	–10.71	–4.72 *	–.00 *	–.00	.00 †	.00	–.00 †	–11.73	–4.53 *	–.00 *
		(11.97)	(2.34)	(.00)	(.00)	(.00)	(.00)	(.00)	(11.06)	(2.17)	(.00)
Constant		721.97 ***	98.55 **	.06 ***	.05 ***	.02 ***	.09 ***	.08 ***	754.12 ***	86.11 **	.03 ***
		(182.54)	(35.63)	(.01)	(.00)	(.01)	(.01)	(.01)	(168.93)	(33.08)	(.00)
R^2		.37	.17	.11	.72	.11	.09	.09	.46	.29	.44
N		3,972	3,972	3,937	3,937	3,937	3,937	3,478	3,968	3,968	3,933
dfres		82,025.1	68,898.2	–2,487.5	–3,884.5	–567.1	–1,029.1	–3,028.9	81,413.5	68,313.9	–4,307

Note: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$)

Appendix A (I) (B): Regression coefficients for difference models - Results for alternative circumference (5km) – Unstandardized

		Gross Sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	.22 ***	.11 ***	–.01	.29 ***	–.19 ***	–.02	.04	.15 ***	.11 ***	–.04 †
		(.02)	(.03)	(.03)	(.02)	(.03)	(.03)	(.03)	(.02)	(.02)	(.02)
	Pulse Dummy (+ 2 weeks)	–.02	–.04 **	–.03 †	.04 ***	.04 *	.04 *	.04 †	–.04 ***	–.04 **	–.03 *
		(.01)	(.02)	(.02)	(.01)	(.02)	(.02)	(.02)	(.01)	(.02)	(.01)
	Post Open Week Dummy	–.07 **	–.07 **	.03	.21 ***	.13 ***	.18 ***	.12 ***	–.17 ***	–.04 †	.05 *
		(.02)	(.03)	(.03)	(.02)	(.03)	(.03)	(.03)	(.02)	(.02)	(.02)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	.29 ***	–.15 ***	–.24 ***
									(.02)	(.02)	(.02)
	Share Returns	—	—	—	—	—	—	—	.11 ***	–.33 ***	–.58 ***
									(.01)	(.02)	(.02)
	Share of Sensory Products	—	—	—	—	—	—	—	.11 ***	.33 ***	.57 ***
									(.02)	(.02)	(.02)
	Share of New Customers	—	—	—	—	—	—	—	.01	.04 **	.07 ***
									(.01)	(.02)	(.01)
Controls	Holiday Dummy	–.01	–.03 *	–.05 ***	.00	.05 ***	–.01	–.01	–.02 †	–.02	–.01
		(.01)	(.02)	(.02)	(.00)	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)
	Sun Hours	.03 †	–.02	–.06 **	–.04 **	.05 *	–.00	–.03	.04 *	–.03 †	–.04 **
		(.02)	(.02)	(.02)	(.01)	(.02)	(.00)	(.02)	(.02)	(.02)	(.02)
	Rainfall	–.01	–.03 *	–.03 *	–.01	.03 †	.02	–.04 †	–.01	–.03 *	–.03 *
		(.01)	(.02)	(.02)	(.01)	(.02)	(.02)	(.02)	(.01)	(.02)	(.01)
R^2		.37	.17	.11	.72	.11	.09	.09	.46	.29	.44
N		3,972	3,972	3,937	3,937	3,937	3,937	3,478	3,968	3,968	3,933
dfres		9,596	10,703.4	10,896.1	6,192.4	10,934.7	11,020.9	9,746.9	8,984.4	10,119.1	9,076.5

Note: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$)

Appendix A (II) (B): Regression coefficients for difference models - Results for alternative circumference (5km) - Standardized

		Gross Sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	1,343.95 ***	147.85 ***	–.02 †	.12 ***	–.06 ***	–.03 *	–.00	992.59 ***	100.63 **	–.02 **
		(162.28)	(35.70)	(.01)	(.01)	(.01)	(.01)	(.00)	(149.45)	(31.77)	(.01)
	Pulse Dummy	–151.64	–71.44	–.01	.08 ***	.04 †	.08 **	.08 ***	–838.78 *	–123.02 †	–.02
	(+ 2 weeks)	(377.59)	(83.05)	(.02)	(.01)	(.03)	(.03)	(.02)	(343.89)	(73.10)	(.02)
	Post Open Week	–4.57	–1.72	.00 **	.00 ***	.00 **	.00 ***	.00 ***	–27.06 ***	–1.83 †	.00
	Dummy	(4.95)	(1.09)	(.00)	(.00)	(.00)	(.00)	(.00)	(4.56)	(.97)	(.00)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	5,524.20 ***	–286.22 ***	–.11 ***
									(279.95)	(59.51)	(.02)
	Share Returns	—	—	—	—	—	—	—	3,423.99 ***	–1,431.72 ***	–.47 ***
									(148.49)	(31.56)	(.01)
	Share of Sensory Products	—	—	—	—	—	—	—	2,277.90 ***	1,200.68 ***	.52 ***
									(129.33)	(27.49)	(.01)
	Share of New Customers	—	—	—	—	—	—	—	722.04 ***	181.24 ***	.08 ***
									(158,82)	(33.76)	(.01)
Controls	Holiday Dummy	–43.57	–49.85	–.02 †	–.00	.02 *	–.00	.01	–46.67	–23.05	–.00
		(141.43)	(31.11)	(.01)	(.00)	(.01)	(.00)	(.01)	(128.64)	(27.34)	(.00)
	Sun Hours	–.78	–1.04	–.00 ***	–.00 ***	.00	–.00	–.00 **	–2.44	–1.18 †	–.00 ***
		(3.20)	(.70)	(.00)	(.00)	(.00)	(.00)	(.00)	(2.91)	(.62)	(.00)
	Rainfall	–5.67	–2.00 *	–.00 **	.00	.00 †	.00	–.00	–6.74 †	–1.51 †	–.00 **
		(4.25)	(.94)	(.00)	(.00)	(.00)	(.00)	(.00)	(3.87)	(.82)	(.00)
Constant		–12.12	16.51	.07 ***	.03 ***	.06 ***	.11 ***	.11 ***	94.69	26.95 †	.04 ***
		(82.25)	(18.09)	(.01)	(.00)	(.01)	(.01)	(.00)	(74.85)	(15.91)	(.00)
R^2		.33	.09	.04	.61	.04	.04	.08	.44	.30	.32
N		11,281	11,281	10,949	10,949	10,949	10,949	8,803	11,277	11,277	10,945
dfres		227,048.1	192,524.6	6,462.1	–9,821.5	6,978,3	7,558.7	397.1	224,912.9	189,609.8	2,602.6

Note: † p < .10, * p < .05, ** p < .01, *** p < .001)

Appendix B (B): One-to-one matching regression coefficients

		Gross sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	1,298.27 *** (177.08)	163.34 *** (32.21)	–.05 *** (.01)	.20 *** (.01)	–.10 *** (.01)	–.00 (.00)	–.00 (.00)	579.22 *** (163.20)	116.89 *** (29.68)	–.03 *** (.01)
	Pulse Dummy (+ 2 weeks)	–438.19 (411.41)	–92.98 (74.83)	.02 (.02)	.03 * (.02)	.06 ** (.02)	.07 *** (.02)	.06 *** (.02)	–1,078.96 ** (374.45)	–112.60 † (68.10)	.02 (.01)
	Post Open Weeks	–5.96 (5.41)	–2.07 * (.98)	.00 *** (.00)	.00 *** (.00)	.00 *** (.00)	.00 *** (.00)	.00 *** (.00)	–34.94 *** (4.97)	–0.50 (.90)	.00 *** (.00)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	9,010.11 *** (296,97)	–561.48 *** (54.01)	–.30 *** (.01)
	Share Returns	—	—	—	—	—	—	—	2,856.83 *** (206.76)	–1,440.76 *** (37.60)	–.45 *** (.01)
	Share of Sensory Products	—	—	—	—	—	—	—	3,197.39 *** (179.50)	1,247.79 *** (32.65)	.50 *** (.01)
	Share of New Customers	—	—	—	—	—	—	—	101.92 (214,81)	152.11 *** (39.07)	.08 *** (.01)
Controls	Holiday Dummy	–136.06 (154.13)	–80.21 ** (28.03)	–.02 *** (.01)	–.01 (.01)	.03 *** (.01)	–.01 (.01)	.00 (.00)	–193.98 (140.21)	–44.38 † (25.50)	–.01 (.01)
	Sun Hours	–17.88 *** (3.26)	–2.34 *** (.59)	–.00 *** (.00)	–.00 *** (.00)	.00 *** (.00)	.00 (.00)	.00 (.00)	–13.17 *** (2.97)	–1.78 *** (.54)	.00 * (.00)
	Rainfall	–34.57 *** (5.59)	–4.32 *** (1.02)	–.00 (.00)	–.00 *** (.00)	.00 *** (.00)	.00 † (.00)	.00 ** (.00)	–30.39 *** (5.08)	–3.34 *** (.93)	.00 (.00)
Constant		136.99 (91.89)	42.37 * (16.71)	.08 *** (.00)	.02 *** (.00)	.04 *** (.00)	.10 *** (.00)	.11 *** (.00)	178.58 * (83.68)	42.09 ** (15.22)	.05 *** (.00)
R²		0.02	0.01	0.01	0.31	.02	.02	.01	.19	.18	.35
N		11,529	11,529	11,182	11,182	11,182	11,182	9,009	11,525	11,525	11,178
dfres		231,928.6	192,603.9	–2,633.6	–3,661.4	1,513	128.9	–4,146.1	229,767.1	190,441.6	–7,327.8

Note: † p < .10, * p < .05, ** p < .01, *** p < .001)

Appendix C (I) (B): Pooled OLS-regression coefficients for difference models – Unstandardized

		Gross sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	.12 *** (177.09)	.08 *** (32.21)	–.11 *** (.01)	.41 *** (.01)	–.19 *** (.01)	–.01 (.01)	–.01 (.01)	.05 *** (163.20)	.06 *** (29.68)	–.07 *** (.01)
	Pulse Dummy (+ 2 weeks)	–.01 (411.41)	–0.01 (74.83)	.01 (.02)	.02 * (.02)	.03 ** (.02)	.04 *** (.02)	.04 *** (.02)	–.03 ** (374.45)	–.02 † (68.10)	.01 (.01)
	Post Open Weeks	–.02 (5.41)	–.03 * (.98)	.10 *** (.00)	.16 *** (.00)	.11 *** (.00)	.13 *** (.00)	.11 *** (.00)	–.10 *** (4.97)	–.01 (.91)	.14 *** (.00)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	.29 *** (296.97)	–.10 *** (54.01)	–.34 *** (.01)
	Share Returns	—	—	—	—	—	—	—	.14 *** (206.76)	–.39 *** (37.60)	–.54 *** (.01)
	Share of Sensory Products	—	—	—	—	—	—	—	.19 *** (179.50)	.41 *** (32.65)	.56 *** (.01)
	Share of New Customers	—	—	—	—	—	—	—	.00 (214.81)	.04 *** (39.07)	.08 *** (.01)
Controls	Holiday Dummy	–.01 (154.13)	–.03 ** (28.03)	–.03 *** (.01)	–.01 (.01)	.04 *** (.01)	–.01 (.01)	–.00 (.00)	–.01 (140.21)	–.02 † (25.50)	–.01 (.01)
	Sun Hours	–.05 *** (3.26)	–.04 *** (.59)	–.04 *** (.00)	–.08 *** (.00)	.08 *** (.00)	–.01 (.00)	.00 (.00)	–.04 *** (2.97)	–.03 *** (.54)	–.02 * (.00)
	Rainfall	–.06 *** (5.59)	–.04 *** (1.02)	–.00 (.00)	–.03 *** (.00)	.04 *** (.00)	.02 † (.00)	.03 ** (.00)	–.05 *** (5.08)	–.03 *** (.93)	.00 (.00)
R^2		.02	.01	.01	.03	.02	.02	.01	.19	.18	.35
N		11,536	11,536	11,189	11,189	11,189	11,189	9,016	11,536	11,536	11,189

Note: † p < .10, * p < .05, ** p < .01, *** p < .001)

Appendix C (II) (B): Pooled OLS-regression coefficients for difference models – Standardized

		Gross Sales	Operating Profit	Operating Profit Margin	Share of Offline Sales	Share of Returns	Share of Sensory Products	Share of New Customers	Gross Sales	Operating Profit	Operating Profit Margin
Independent variables		1a	1b	1c	2a	2b	2c	2d	3a	3b	3c
Opening dummies	Step Dummy	.10 *** (.01)	.08 *** (.02)	–.04 ** (.02)	.25 *** (.01)	–.13 *** (.02)	–.04 ** (.02)	.01 (.02)	.07 *** (.01)	.05 *** (.01)	–.07 *** (.01)
	Pulse Dummy (+ 2 weeks)	–.00 (.00)	–.01 (.01)	.00 (.00)	.04 *** (.01)	.02 * (.01)	.04 *** (.01)	.03 ** (.01)	–.01 (.01)	–.02 * (.01)	–.01 (.01)
	Post Open Week Dummy	.01 (.01)	–0.03 * (.02)	.06 *** (.02)	.23 *** (.01)	.09 *** (.02)	.15 *** (.02)	.09 *** (.02)	–.06 *** (.01)	–.02 (.01)	.05 *** (.01)
Drivers	Share Offline Sales	—	—	—	—	—	—	—	.17 *** (.01)	–.06 *** (.01)	–.13 *** (.01)
	Share Returns	—	—	—	—	—	—	—	.16 *** (.01)	–.39 *** (.01)	–.58 *** (.01)
	Share of Sensory Products	—	—	—	—	—	—	—	.14 *** (.01)	.40 *** (.01)	.58 *** (.01)
	Share of New Customers	—	—	—	—	—	—	—	.03 *** (.01)	.03 *** (.01)	.05 *** (.01)
Controls	Holiday Dummy	–.00 (.01)	–.03 ** (.01)	–.04 *** (.01)	–.00 (.00)	.03 *** (.01)	–.01 (.01)	–.00 (.00)	–.01 (.01)	–.02 † (.01)	–.01 (.01)
	Sun Hours	.01 (.01)	–.03 ** (.01)	–.08 *** (.01)	–.04 *** (.01)	.04 *** (.01)	–.02 † (.01)	–.06 *** (.01)	.01 (.01)	–.03 ** (.01)	–.04 *** (.01)
	Rainfall	–0.02 * (.01)	–.03 ** (.01)	–.03 ** (.01)	–.01 (.01)	.02 † (.01)	.01 (.01)	–.02 (.01)	–.02 * (.01)	–.03 *** (.01)	–.02 ** (.01)
R^2		.37	.13	.06	.61	.07	.05	.12	.46	.30	.41
N		11,418	11,418	11,071	11,071	11,071	11,071	8,898	11,414	11,414	11,067
dfres		27,555.8	31,217.7	31,090.2	21,339.6	30,992.8	31,225.1	24,507.2	25,761.5	28,791.4	25,898.3

Note: † p < .10, * p < .05, ** p < .01, *** p < .001)

Appendix D (B): Standardized regression coefficients for difference models

DV		**Mediator**							
		Share of Offline Sales		**Share Returns**		**Share of Sensory Products**		**Share of New Customers**	
	Week	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Gross Sales	Week 2	**519.599**	**866.667**	**–277.703**	**–153.418**	**–72.730**	**–6.528**	–4.078	12.013
	Week 25	**878.247**	**1,348.521**	**–157.298**	**–79.737**	**55.643**	**104.068**	**9.538**	**28.047**
	Week 51	**1,269.171**	**1,912.173**	–71.079	56.859	**171.038**	**257.304**	**18.783**	**52.482**
Operating Profit	Week 2	**–62.577**	**–17.733**	**67.446**	**127.080**	**–36.979**	**–3.119**	–0.766	2.559
	Week 25	**–99.000**	**–28.640**	**36.056**	**71.091**	**28.459**	**53.248**	**1.917**	**5.913**
	Week 51	**–142.205**	**–41.826**	–26.914	30.986	**88.444**	**130.591**	**3.795**	**11.161**
Operating Profit Margin	Week 2	**–.018**	**–.011**	**.022**	**.042**	**–.015**	**–.001**	**.000**	**.001**
	Week 25	**–.029**	**–.018**	**.012**	**.023**	**.012**	**.022**	**.001**	**.003**
	Week 51	**–.041**	**–.025**	–.009	.010	**.037**	**.055**	**.002**	**.005**

Note: bias-corrected, 95% CI, n = 5,000 for indirect effects; bold values are significant on a 5%-level

Appendix E (B): Confidence intervals for the mediation analysis

II. Website Cookies and Consumer Reactions – Implications for Online Marketing and Public Policy

1 Introduction

Within retailers‘ multichannel systems, the online channel occupies a special position: compared to other channels such as brick-and-mortar stores or catalog, this channel is very young and develops particularly dynamically. In the US, already today, retail e-commerce sales account for roughly 11% of total retail sales (U.S. Department of Commerce 2019). This number is even expected to increase in the future and to extend to other geographies (Young 2019). Therefore, the online channel has become very dominant and is considered as a disruptive development (Christensen and Raynor 2013). The remaining part of this dissertation will focus on this specific channel.

The example of the rapid rise of the online channel shows that companies are subject to continuous change. New technologies offer them a range of opportunities such as electronic sales channels or digital marketing communication that can be utilized to address consumers in a targeted manner.

Yet, not only companies and their offerings adapt to continuous technological progress, but also consumer behavior is changing (Verhoef, Kannan, and Inman 2015a). For example, consumers pay decreasing attention to various marketing activities on different channels due to sensory overload (Johannes et al. 2019; Wilmer, Sherman, and Chein 2017). Thus, established effect relations between marketing activities and economic success become increasingly complex, posing a major challenge for many companies. It is, therefore, of great relevance to better understand the effects of new technologies on the interdependencies of marketing and consumer behavior (Sheth, Mittal, and Newman 2002). This part of the cumulative dissertation project focuses on one specific new technology, website cookies, and examines the consequences of this technology for marketing.

Cookies represent an essential technology for a wide range of online players, including retailers, publishers, and ad networks. Cookies keep track of the consumers’ movements within a company’s website. Companies, in turn, can use this information to identify sources of customer traffic and their behavior on the website (e.g., through Google Analytics), adjust their offering (e.g., price change for returning visitors) or advertise in a more targeted way.

Driven by a public discussion on data privacy, however, recent regulatory changes (e.g., in the European Union: General Data Protection Regulation (GDPR)) intend to set stricter boundaries with respect to how companies can gather information through cookies. Such regulatory changes in the EU also extend to other geographies (Lahiri 2018), and similar regulations are even discussed in the United States (Schechner and Peker 2018). Many online players see this as a serious threat to their business models (Downes 2018).

Nevertheless, website operators still have considerable leeway in the implementation of their cookie notifications (i.e., notifications informing website users about the usage of cookies; van Bavel and Rodríguez-Priego 2016), though latest court rulings (Court of Justice of the European Union 2019) and anticipated regulation (e.g., European Parliament and Council 2017) may restrict this leeway in the future. The current leeway in the implementation leads to a plethora of different cookie notifications (or notices; both terms are used interchangeably in the following), which differ on several dimensions (e.g., visibility and choice; see Article D). Within the legal framework, companies, therefore, will have to decide how they want to design and implement cookie notifications in the future. Anticipated consumer reactions to various cookie notifications are essential to this decision. So far, however, little is known about such reactions, so that there is no sufficient basis for managers to make informed decisions concerning cookie implementation. This dissertation addresses this issue by explicitly focusing on consumer reactions to different cookie notifications. Cookie notifications may differ on several dimensions, one of central importance is choice, that is, the power of consumers to decide whether (and if so, which) data is collected. This dimension is central because consumer behavior data on websites is an extremely valuable resource (Hedderly 2017). In this respect, it is not surprising that companies have tried to give as little choice as possible to consumers in order to collect as much data as possible. With this dissertation project, we extend this view by establishing increased fairness perceptions through attribution (Article D) and decreased risk perceptions through increased power (Article C) as possible positive consequences of choice. Thus, offering consumers an explicit choice over their data no longer becomes a pure matter of avoidance, which companies are forced to comply with by law. Instead, a balancing decision for managers arises: potentially losing a part of the consumer data vs. potentially creating positive affective and behavioral consequences for website visitors.

2 Present Research Project

2.1 Overview of Articles

	Article C	**Article D**
Title	The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy – The Example of Cookie Notices	The Effect of Privacy Choice in Cookie Notices on Consumers' Perceived Fairness of Dynamic Pricing
Research focus	Online channel	Online channel
Co-Authors	Lennard Schmidt, Erik Maier	Lennard Schmidt, Erik Maier
Own contribution	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, data collection, writing article	Main responsibility: Data analysis Shared responsibility: Theoretical development, Research design, data collection, writing article
Publication status	Published in: Journal of Public Policy & Marketing (VHB-JOURQUAL 3: B) Bornschein, R., Schmidt, L., & Maier, E. (2020). The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy: The Example of Cookie Notices. Journal of Public Policy & Marketing, 39(2), 135–154. https://doi.org/10.1177/0743915620902143	Published in: Psychology and Marketing (VHB-JOURQUAL 3: B) Schmidt, L., Bornschein, R., & Maier, E. (2020). The effect of privacy choice in cookie notices on consumers' perceived fairness of frequent price changes. Psychology & Marketing. https://doi.org/10.1002/mar.21356

Table 3: Overview of articles – Part II of the dissertation

2.2 Summary Article C

Research motivation and objective: Recent regulation in the European Union (i.e., the General Data Protection Regulation) aims to give consumers power over their private information through cookie notifications. Specifically, the regulation addresses two dimensions: websites must (1) provide visible notice what consumer information they collect through cookies and (2) allow consumers the choice to not consent to such tracking (European Parliament and Council 2016). Such choice would increase consumers' objective power over their data. Anecdotic evidence and interviews with managers suggest, however, that there exists considerable leeway with respect to the implementation of the regulation, resulting in a plethora of different cookie notifications. First, we must understand whether and how strongly the implementation differs. Second, visibility and choice are likely to influence consumers' perceived power over their private information. Private data is a resource over which website operators can have power (Acquisti, Brandimarte, and Loewenstein 2015); and this power relationship needs further investigation (Labrecque et al. 2013). Therefore, this research investigates the implementation of the new cookie regulation and its effect on consumers' perceived power over their private information, as well as the latter's moderators, unintended side effects (i.e., risk perceptions), and affective and behavioral consequences.

Methodology: We conduct a content analysis to assess the implementation of the EU cookie regulation among a representative sample of 343 websites. With four experimental studies (including a representative sample of German internet users), we analyze consumers' reactions to cookie notifications that vary in visibility and choice, using mediation analysis.

Main findings: The content analysis shows that websites' cookie notifications often do not offer a choice over the data collection. Additionally, the visibility of the cookie notices is often low. Four experimental studies explore the effects of the two dimensions (notice visibility and choice) and show that while offering choice over whether or which data are used increases perceived power, visibility of the notice (vs. no notice) only affects consumers' risk perceptions. Perceived risk is mitigated if consumers have more choice over their data (indirectly through greater power). Age moderates these relationships. Power and risk, in turn, influence consumer affect and purchase intent.

Contribution: Our research theoretically contributes to the literature by formally introducing and testing the construct of perceived power to research on consumer information privacy (e.g., Markos, Milne, and Peltier 2017; Martin 2015; Milne and Gordon 1993), thus answering calls for research (Labrecque et al. 2013; Stewart 2015; Milne and Bahl 2010). Specifically, we establish cookie notifications, which influence control over consumers' private information, as another antecedent to power. Further, we document age as a moderator of perceived power, a construct, which to date has only been identified in the adoption literature (Chung et al. 2010). We conceptually extend previous works on privacy regulation in the European Union (Goldfarb and Tucker 2011), in that we distinguish between visible notice about website practices with privacy implications and choice about how these practices are conducted. We, thus, contribute to the notice vs. choice debate (e.g., Acquisti, Brandimarte and Loewenstein 2015). Finally, we establish perceived risk as a side effect of the visibility of cookie notifications that can be mitigated through perceptions of increased power from choice over the data collection.

2.3 Summary Article D

Research motivation and objective: Many industry players critically eye recent legislative attempts to strengthen consumer's data privacy (e.g., the General Data Protection Regulation; Downes 2018). In particular, they criticize the calls for explicit consent of consumers with the use of cookies. Many online players fear the loss of valuable customer data and, thus, try to avoid consumer choice with respect to cookies as far as possible (see Article C). However, little is known about consumers' reactions to different cookie policies (Miyazaki 2008; Martin 2015), especially about potential positive consequences of implementing cookies that give consumers a choice. This article addresses this gap by investigating consumers' reactions to price discriminatory activities depending on different cookie notifications

Methodology: With two experimental studies, we analyze consumers' reactions to different cookie notifications that vary in choice, using mediation analysis.

Main findings: Our results indicate that the regulation of cookie notifications, and its implementation with actual consent, might have also positive consequences for retailers: the more actively a consumer agrees to the use of cookies, the more they attribute potential discriminatory actions based on these cookies (here: price changes) to themselves, increasing fairness perceptions and purchase intent.

Contribution: Article D contributes to extant research in multiple ways. First, we introduce attribution theory to the investigation of privacy decision making. Thereby, our research helps to complement a holistic framework for researching customers' privacy decisions. Second, we establish consent in privacy decision-making as an antecedent of price fairness and purchase intent. This adds to research on price fairness in online context and involvement in the price-setting process (e.g., Haws and Bearden 2006), establishing also indirect forms of involvement (i.e., agreeing with the usage of cookies). Finally, we establish downstream consequences of choice in consumer privacy decision-making, which are relevant for managers and policy makers alike. The investigation of the consequences of consumer privacy choice is more than ever relevant. In the light of recent regulation (e.g., GDPR in Europe), companies face a trade-off between collecting consumer data (i.e., to develop personalized offerings) and giving control to consumers (i.e., to comply with regulation). At the same, time dynamic pricing strategies are increasing. This investigation contributes to a better understanding of consumers' attributions in the formation of price fairness perceptions.

3 Article C: The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy – The Example of Cookie Notices

Abstract

Recent regulation in the European Union (i.e., the General Data Protection Regulation: GDPR) affects websites' information privacy practices. This regulation addresses two dimensions: websites must (1) provide visible notice about which private information they collect through cookies and (2) allow consumers the choice to disagree to such tracking. Policy makers need to understand the degree of implementation of their regulation, but also its effect on consumers. We develop a typology of website cookie notices along the dimensions notice visibility and choice. A field study shows that most websites only offer low notice visibility and limited choice over the collection of private information. In addition, four experimental studies in the EU and United States explore the effects of information privacy practices: while offering choice over whether or which data are used increases consumer power, visibility of the notice (vs. no notice) only affects risk perceptions. We establish the novel suggestion that perceived risk is mitigated if consumers have more choice over their data (indirectly through greater power). Power and risk influence consumers' affect and purchase intent.

Publication status

Published in: Journal of Public Policy & Marketing (VHB-JOURQUAL 3: B)

Bornschein, R., Schmidt, L., & Maier, E. (2020). The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy: The Example of Cookie Notices. Journal of Public Policy & Marketing, 39(2), 135–154.

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4 Article D: The Effect of Privacy Choice in Cookie Notices on Consumers' Perceived Fairness of Dynamic Pricing

Abstract

Recent regulatory changes (i.e., General Data Protection Regulation of the European Union [GDPR]) enforce that seller (e.g., retail and service) and all other websites disclose through cookie notices which data they collect and store. At the same time, websites must allow consumers to disagree to the tracking of their browsing behavior. Despite sellers' concern about the loss of consumer insights – as consumers might disagree to the collection of their browsing data – cookie notices might also have a surprising side-effect: Consumers might accept frequent price changes (from personalized or dynamic pricing) more readily, if they agree that their behavior can be tracked. Specifically, two experimental studies show that consent to the tracking of browsing behavior increases consumers internal attribution of a price change, as consumers attribute the cause of the change (here: giving up data) to themselves. This increases price fairness perceptions and, in turn, purchase intent. As a result, for online sellers of goods or services the implementation of cookie notice should no longer be thought as a matter to be avoided, but rather a trade-off decision: loss of a part of consumer insights versus higher acceptance of data-driven marketing mix decisions, such as frequent price changes.

Publication status

Published in: Psychology and Marketing (VHB-JOURQUAL 3: B)

Schmidt, L., Bornschein, R., & Maier, E. (2020). The effect of privacy choice in cookie notices on consumers' perceived fairness of frequent price changes. Psychology & Marketing.

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Concluding Remarks

The overarching aim of this thesis is to contribute to a better understanding of the complex relationships in a multichannel context. Specifically, it strives to create a more detailed understanding of (a) consumer behavior and (b) consequences of managerial decisions in a multichannel context to enable better-informed managerial decision-making. The individual articles, as well as the corresponding summaries, already provide a detailed insight into the respective contributions and, therefore, should give an impression on how the individual articles contribute to this overarching aim. This section only briefly discusses the main contribution, limitations of this dissertation project, and outlines some possible avenues for future research.

The first part of this dissertation covers each of the two major research streams within the multichannel literature (consumer stream and company stream; Shareef, Dwivedi, and Kumar 2016; Verhoef 2012) with one article. Article A extends our understanding of the antecedents of an under-researched form of research shopping, webrooming, and is the first study to shed light on the interplay of channel and retailer aspects, as they are likely to occur in real shopping situations.

Article B enhances our understanding of the effects of managerial decisions in a multichannel context (i.e., offline channel addition) on key business figures (i.e., revenue, absolute profit, and profit margin). Specifically, it contributes to the multichannel literature by adding a new dimension to the discussion on offline channel additions: profitability. It is the first article to show empirically profitability effects of a store opening, establish drivers of these effects, and investigate segment-specific effects of channel additions for profitability.

The second part of this dissertation focuses on one specific channel within the multichannel context, the online channel, and examines consumer reactions to a new online technology: cookies. Both articles offer implications for researchers, managers, and policy makers alike. First, the content analysis of Article C shows that websites' cookie notifications often are poorly visible and do not offer a choice over the data collection. This snapshot is relevant for website operators (e.g., for benchmarking purposes) as well as for policy makers (e.g., as a starting point for the evaluation processes). Second, the experimental studies of Article C and Article D expand our understanding of consumer reactions towards varying cookie notifications. They, therefore, provide insights for (a) website operators on how to utilize the considerable legal leeway in the implementation of their cookie notifications and (b) policy makers on how certain cookie notifications affect the well-being of consumers.

In summary, one can cautiously agree that this work has achieved its aim, that is, to contribute to a better understanding of the complex relationships in a multichannel system. Like any work, this dissertation is subject to certain limitations, which are briefly discussed below. Again, detailed statements on limitations and future research can already be found in the individual articles. The limitations of the four articles will be clustered here into three main categories: generalizability, informative value, and methodological variance. First, all articles have - to various degrees - limited generalizability. The limited generalizability follows from the selected foci for the respective empirical studies, such as geographies (e.g., Article A, Article B: Germany), industries (e.g., Article A: consumer electronics, Article C: clothing, Article D: airlines), number of retailers/stores (Article B). To further extend the generalizability of the findings it would be necessary to examine similar studies in different contexts (e.g., geographies, industries) and increase the number of research objects (i.e., number of retailers/stores in Article B), which, however, is infeasible within the scope of one dissertation project. Second, some of the dependent variables in the second part of the thesis (i.e., purchase intention) have only limited relevance for the intended readership (i.e., managers). Statements of consumers concerning behavioral intentions have only limited informative value, as they often do not correspond to real behavior (Sheeran and Webb 2016; Rhodes and Bruijn 2013). This frequently encountered limitation results from the comparatively high resource expenditure required to obtain real behavioral data. Article A and Article B address this point, however, by leveraging survey responses referring to consumers' past purchases (Article A) and real transaction data (Article B). Third, the entire dissertation draws predominantly on quantitative data, which are compared and reflected in the course of existing literature. Nevertheless, a more qualitative approach would certainly constitute a valuable extension to the methodology applied here - especially in order to discover new contexts that are not currently available in the literature.

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