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When Online Meets Offline: Research in Omni-Channel Marketing

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When Online Meets Offline: Research in Omni-Channel Marketing

Lisan Lesscher

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Lisan

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Chapter 1

Introduction

1.1. How digitalization affected consumers, businesses and marketing

We are living in a digital era. It is almost impossible to imagine our everyday life without digital technologies. We connect with each other through our smartphones and work with computers¹. Globally, there are more than 4.5 billion active internet users and this number continues to grow annually (Data Reportal, 2020). Furthermore, we are used to purchasing online and using multiple touchpoints in our path to purchase (e.g., Herhausen et al., 2019; Lemon and Verhoef, 2016). Online sales worldwide also tremendously increased over the past years reaching sales of over 3500 billion U.S. dollars (Statistica, 2020). Whereas it is almost impossible to imagine living *without* being digital nowadays, it was nearly impossible to imagine living *with* these digital technologies a quarter of a century ago.

The advent of digital technologies, leading to the ongoing digitalization, mainly influenced this shift from being almost impossible to imagine living *with* these digital technologies to being nearly impossible to imagine living *without* being digital. This entrance brought a lot of change forcing business and marketing to transform drastically. Starting with the introduction and worldwide adoption of the Internet and World Wide Web in the late 90's of the last century together with the rise of an increasing number of accompanying technologies (e.g., smartphones, SEO, online payment systems), the development of e-commerce strengthened. Furthermore, the term *digital marketing* developed and evolved over time. From a specific term representing the use of digital channels for the marketing of products and services to an umbrella term as defined by Kannan and Li (2017, p. 3): “an adaptive, technology-enabled process by which firms collaborate with customers and partners to jointly create, communicate, deliver, and sustain value for all stakeholders.” The fast growth of digital marketing attracted much attention from marketing researchers, whose main interest was to explore how the proliferation of new channels affects consumers' purchase behavior and strategies (for a review,

¹ In times of a pandemic, which we faced the past months, we are especially very thankful for this. The digital era allowed us to move online and continue working and interacting with one another.

see Kannan and Li, 2017). All in all, the changes have far-reaching impact on consumers on the one hand, and business and marketing on the other hand.

1.1.1. The impact of digitalization on consumers

The digitalization affected consumers since the ways of communicating, gathering and exchanging information about products/services, and obtaining and consuming them drastically changed as well (e.g., Hennig-Thurau et al., 2010). After the introduction of digital technologies, a plethora of new media have made their entrance. Like Verhoef et al. (2020) suggest, this provided consumers with opportunities to become more active, connected, empowered and informed (e.g., Lamberton and Stephen, 2016; Verhoef et al., 2017). Also, Hennig-Thurau et al. (2010) indicate that consumers are provided with wide-ranging options to provide information: “the digital innovations of the last decade made it effortless, indeed second nature, for audiences to talk back and talk to each other” (Deighton and Kornfeld, 2009, p. 4). For example, digital technologies enable consumers to help other consumers by sharing product reviews or to co-create value by designing and/or customizing products (e.g., Beckers, Van Doorn, and Verhoef, 2018; Grönroos and Voima, 2013). Also, consumers are empowered by the new media to promote and distribute their own offers. You can think of consumers as retailers on eBay or the Dutch Marktplaats, but also consumers as producers or advertisers on YouTube.

1.1.2. The impact of digitalization on business and marketing

Apart from affecting consumers, the digitalization also influenced business and marketing – also (partly) due to its effect on consumers provoking the need for change in business and marketing (e.g., consumer centric perspective). The (new) digital technologies change all aspects within firms, from their activities, to the processes, systems and structures. Therefore, business models also have changed, and keep on changing, based on the digital developments. A new type of business model termed *digital business model* was introduced, which Verhoef

and Bijmolt (2019) define as “situations where digital technologies have fundamentally affected the way a firm structures and carries out its business and thereby creates value for customers, the firm itself, and its partners” (based on Martín-Peña, Díaz-Garrido, and Sánchez-López, 2018).

Overall, the digitalization impacted consumers, business and marketing to a large extent, as outlined here. It provided both firms and consumers with a number of opportunities, but also complexity in terms of channel management highly increased. However, a key question that remains now that “online and offline have met” is: what happens to offline after the introduction of online?

1.1.3. From multichannel to omnichannel

Before the introduction of online, one of the very few options for consumers to purchase was to go to a brick-and-mortar store. Firms had the opportunity to have one-way directed communication via direct marketing instruments (e.g., direct mail or catalogue) delivered to consumers’ homes or via mass communication media (i.e. television, radio and print advertising) (Kotler and Armstrong, 2018). As indicated by Kotler and Armstrong (2018, p. 512), direct marketing, such as direct mailing, concerns “engaging directly with carefully targeted individual consumers and customer communities to obtain both an immediate response and build lasting customer relationships.” On the other hand, mass marketing communications presented a market-coverage strategy where the firm reached out to the whole market while ignoring market segments and their differences. In general, the channels available for firms and consumers to purchase and communicate products and/or services were rather limited and geographically bound (compared to the situation we know now).

With the introduction of the Internet, online sales channels started to appear as well as ways to communicate online with customers. The online channels (for communication or distribution) co-existed with the offline channels (from before the rise of online). With all

changes based on the introduction of online (i.e., the changed business model with the new channels and changing consumer behavior), retailers initiated multichannel strategies (either for communication or distribution). These multichannel strategies mainly deal with whether new channels should be included in the existing channel mix (e.g., Deleersnyder et al., 2002). This decision applies not only to the traditional brick-and-mortar firms, but also to new online-only firms (Avery et al., 2012). Over time, the scope of multichannel retailing extended to, for example, the management of customers across multiple channels (e.g., Neslin et al., 2006). The article of Neslin et al. (2006, p. 96) has been very influential in the development of research on multichannel retailing, defining multichannel customer management as “the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development.” Important to note is that channels are now considered as a medium for consumers and firms to interact, which focuses on channels providing two-way interaction instead of the former one-way interaction of traditional marketing.

Multichannel strategies (developed based on the growth of online channels and its effect on firms and consumers) have mostly been developed and managed separately within firms (Verhoef, 2012), with only limited integration. When new online and even mobile channels came up, this resulted in another disruptive change to retailing (Rigby, 2011). Apart from more channels that could be studied, the natural borders between channels began to disappear with the different channels becoming blurred. “Channels are interchangeably and seamlessly used during the search and purchase process and it is difficult or virtually impossible for firms to control this usage” (Verhoef, Kannan, and Inman, 2015, p. 175). This is termed omni-channel management (for more information, see Verhoef, Kannan and Inman, 2015), which is defined as “the synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels

is optimized” (Verhoef, Kannan, and Inman, 2015, p. 176). With its entrance, Verhoef, Kannan and Inman (2015) suggest that omni-channel management is put in place for multichannel management.

1.2. Challenges based on digitalization

Altogether, the digitalization affected consumers, business and marketing, as described previously. This presents opportunities, but also comes with challenges (e.g., Leeflang et al., 2014). In this dissertation, we will focus on two out of the four outlined challenges for marketing in a digital era by Leeflang et al. (2014), that is: (1) new ways for firms to communicate with customers (where they focus on social media), and (2) proliferation of channels (for distribution). These challenges represent both the start of a consumers’ purchase journey (i.e., making consumers aware of a firm’s offering) and its end (i.e., consumers purchasing your offering) with communication being the one of the most visible aspects of marketing, which consumers most often associate marketing with, and distribution being the most impactful for (sales) performance (e.g., Ataman, Van Heerde, and Mela, 2010). Furthermore, these challenges also represent two out of the four “P’s” as outlined by Kotler and Armstrong (2018): promotion and place. We will focus on the challenges for marketing in the digital era for both pillars in this dissertation, which we will explain in the following.

1.2.1. Challenge for communication channels

The first foundation of marketing we address is communication, which firms use to promote their products and/or services to consumers. A challenge for marketing in the digital era as stated by Leeflang et al. (2014) concerns communication channels. Explicitly, the challenge by Leeflang et al. (2014) emphasizes social media, which provides a very interesting opportunity for firms to communicate with consumers (e.g., De Vries, Gensler, and Leeflang, 2012; Srinivasan, Rutz, and Pauwels, 2016). Nevertheless, social media is not the only new communication channel provided by the digitalization as the advent of digital technologies has

led to the development of a wide variety of channels – such as e-mail, mobile or websites. Leeflang et al. (2014) also support this as their survey among firms highlights the ability to interact with consumers in a new way to be by far the most dominant change in the past years. From the traditional communication channels, we know their absolute and relative effectiveness in an offline dominated world (e.g., Assmus, Farley, and Lehmann, 1984; Sethuraman, Tellis, and Briesch, 2011). However, insights about the effectiveness of these communication tools in an online environment is still scarce. This particularly holds for insights considering the effects of traditional communication channels throughout the purchase funnel, which implies also considering all stages consumers move through before eventually conducting a purchase (termed the search-purchase funnel or simply purchase funnel; Verhoef et al., 2017). For the new communication channels, research provides insights into how they work in isolation (e.g., Agarwal, Hosanagar, and Smith, 2015; De Haan, Wiesel, and Pauwels, 2016) and the online-to-offline marketing communication effects (e.g., Lobschat, Osinga, and Reinartz, 2017). Notwithstanding, the effectiveness of the traditional together with new communication channels is rather limited. Both limitations are also represented by the Marketing Science Institute's top 1 tier research priorities for 2018-2020 (Marketing Science Institute, 2018): *“Managing promotion across channels: How does omnichannel retailing interact with the purchase funnel, and what are the implications for promotional strategy”*. Hence, good examples for studying this research priority are to investigate the effectiveness of a traditional marketing communication channel (i.e., direct mailing) in the online world as well as the synergy between the traditional marketing communication tool and a digital marketing communication tool (i.e., display advertising), which we cover in chapter 2.

1.2.2. Challenge for distribution channels

The second foundation of marketing we focus on is distribution, which firms use to sell their products and/or services to consumers (i.e., sales channels). Another challenge for marketing

in a digital era according to Leeflang et al. (2014) focuses on the management of different distribution channels. This received considerable attention in the rich tradition of multichannel research. The early majority of research focuses on the likelihood of consumers to purchase through a new channel. Later studies discussed how new channels and a mix of the traditional and new channels affect customer purchase behavior and loyalty. For example, studies indicating that including a new channel increases customer loyalty and firm value based on increased revenue (e.g., Homburg, Vollmayr, and Hahn, 2014; Wallace, Giese, and Johnson, 2004). Essentially, multichannel studies with different contexts provide different findings (for an overview, see Liu, Lobschat, and Verhoef, 2018). Research also looked into multichannel customers and their purchase behavior (e.g., Thomas and Sullivan, 2005; Montaguti, Neslin, and Valentini, 2016) and this led to the general notion that multichannel customers are more profitable, purchase more and spend more (compared to single channel customers) (e.g., Kumar, Bezawada, and Trivedi, 2018). However, more research is required to further understand specific boundary conditions to this general statement (Liu, Lobschat, and Verhoef, 2018, p. 56). This is also highlighted in the research priorities 2018-2020 of MSI: “*Managing Distribution and Demand across Channels*” (Marketing Science Institute, 2018). This links to the question whether all consumers should be multichannel, which we will cover in chapter 3 by considering the moderating roles of brand tier and loyalty tier.

1.3. Outline of this dissertation

In this dissertation, we focus on two challenges introduced with the digitalization: (1) management of different (online and offline) communication channels, and (2) management of different distribution/sales channels. The general aim of this dissertation is to gain a better understanding in dealing with these prominent challenges, which arise when online meets offline. As depicted in figure 1.1, chapter 2 goes into the challenge to manage multiple communication channels in the online world. For that reason, chapter 2 aims to provide insights

into the effectiveness of a traditional marketing communication tool in the online environment as well as into the synergy between a traditional and digital marketing communication tool. Chapter 3 addresses the challenge of multichannel distribution by investigating whether all customers should be multichannel or not. In chapter 4, the main findings are summarized and we discuss theoretical and managerial implications together with ideas for future research. Table 1.1 summarizes each chapter based on their contribution, methodology, data source(s) and findings. In the following, we introduce the studies in each chapter.

1.3.1. Do offline and online go hand in hand? Cross-channel and synergy effects of direct mailing and display advertising

Despite the rise of digital, direct mailing as a marketing communication tool remains relevant (*Forbes*, 2017) and widely applied in practice (Statistica, 2019). This mainly is due to the ability of direct mails to be mentally processed easier than emails (Millward Brown, 2009) and to generate greater brand recall (UK Royal Mail, 2015) as well as higher response rates compared to digital marketing communication (e.g., e-mail, paid search, online display, social media; ANA, 2018). Nevertheless, research into the effectiveness of direct mailing in the online environment is scant. Key questions that remain entail how direct mailing affects different online and offline consumer activity metrics throughout the purchase funnel and how they interact with digital marketing communication tools. This chapter, therefore, investigates these two questions by conducting two studies.

First, we focus on the effect of direct mailing on zip-code level upper, middle, and lower funnel performance metrics over time by analyzing quasi-experimental data from a large European insurance firm. The results reveal that direct mailing significantly influences consumer activity metrics in the online channel (i.e., online search and clicking behavior), in support of cross-channel effects of direct mailing. Moreover, direct mailing is shown to be effective throughout the purchase funnel, both directly and indirectly, with a positive net sales

effect. Second, we study the joint effect of direct mailing and display advertising by analyzing field experiment data from the same insurance firm. The results show positive synergy between direct mailing and display advertising. Therefore, despite the rise of digital, direct mailing still serves as an effective marketing tool, both by itself and in combination with digital marketing.

1.3.2. Should all customers be multichannel? Investigating the moderating role of brand and loyalty tier

The increasing number of sales channels (e.g., Marketing Science Institute 2018-2020) provides firms with the opportunity to reach more consumers and provide them with more convenience. However, it also increases complexity for multichannel management. Existing studies support the (general) notion that a multichannel customer (compared to a single channel customer) is more profitable and thereby a multichannel strategy is more effective (e.g., Montaguti, Neslin, and Valentini, 2016; Kumar, Bezawada, and Trivedi, 2018). However, only one third of marketers are confident in their ability to deliver a promising multichannel strategy (CMO, 2015). Hence, more insights into multichannel effectiveness are required for firms, which is also highlighted by the Marketing Science research priority on managing distribution across channels (Marketing Science Institute 2020-2022). Current studies do not consider what happens to multichannel effectiveness when (1) a firm offers multiple brands (i.e., multi-brand firm), and (2) customer heterogeneity (on loyalty status) is considered. To provide insights into these prevailing issues, this study investigates whether customers using multiple sales channels are always more valuable than single channel customers by studying multichannel effectiveness across brands and customer loyalty tiers.

In contrast to conventional wisdom and prior literature, we show that multichannel customers do not always generate more revenue. Single channel customers (vs. multichannel customers) generate more revenue for the highest-level loyalty tier and for the combinations of highest-level loyalty tier and brand tiers. With these results, we strive to provide previously

elusive insights into how to manage multichannel behavior at the multi-brand firm level. Thereby, we aim to provide firms with a precise understanding of the effectiveness of multichannel marketing in the context of multiple brands and taking into account consumer heterogeneity, and to help with developing a promising multichannel strategy to grow revenue.

Figure 1.1: Overview of dissertation

Table 1.1: Overview of dissertation

	Chapter 2	Chapter 3
Focus	Marketing communication channels	Distribution (sales) channels
Aim(s) / Contribution(s)	<ul style="list-style-type: none"> Investigate the effectiveness of direct mailing in the online environment (i.e., cross-channel effects) Explore whether there is synergy between direct mailing and a digital marketing communication tool (i.e., display advertising) 	<ul style="list-style-type: none"> Investigate multichannel effectiveness across brand tiers and loyalty tiers to find out whether all customers should be multichannel or not. Gain a better understanding of the effectiveness of the multichannel marketing strategy
Main findings	<ul style="list-style-type: none"> Direct mailing significantly influences consumer activity metrics in the online channel, in support of cross-channel effects of direct mailing Direct mailing is shown to be effective throughout the purchase funnel, both directly and indirectly, with a positive net sales effect There is a positive synergy between direct mailing and display advertising 	<ul style="list-style-type: none"> Multichannel strategy generates more revenue, but this is not always the case. Single channel customers (vs. multichannel customers) generate more revenue for the highest-level loyalty tier and combinations of highest-level loyalty tier and brand tiers. Firms should not “force” all customers into being multichannel; rather a more nuanced approach that accounts for brand and loyalty tiers may yield better revenue results.
Methodology	Empirical <ul style="list-style-type: none"> Simultaneous system of equations model Difference-in-difference model Regression models 	Empirical <ul style="list-style-type: none"> Propensity score matching Regression models
Data	Quasi-experiment and field experiment data	Observational data from loyalty program
Data source	International Insurance Firm	International Hotel Group

Chapter 2

Do Offline and Online Go Hand in Hand? Cross-Channel and Synergy

Effects of Direct Mailing and Display Advertising²³

Abstract

Despite the rise of digital, direct mailing as a marketing communication tool remains relevant and widely applied in practice. Nevertheless, research into the effectiveness of direct mailing in the online environment is scant. Key questions that remain entail how direct mailing affect different online and offline consumer activity metrics throughout the purchase funnel and how they interact with digital marketing communication tools. The current chapter, therefore, investigates these two questions by conducting two studies. First, we focus on the effect of direct mailing on zip-code level upper, middle, and lower funnel performance metrics over time by analyzing quasi-experimental data from a large European insurance firm. The results reveal that direct mailing significantly influences consumer activity metrics in the online channel (i.e., online search and clicking behavior), in support of cross-channel effects of direct mailing. Moreover, direct mailing is shown to be effective throughout the purchase funnel, both directly and indirectly, with a positive net sales effect. Second, we study the joint effect of direct mailing and display advertising by analyzing field experiment data from the same insurance firm. The results show positive synergy between direct mailing and display advertising. Therefore, despite the rise of digital, direct mailing still serves as an effective marketing tool, both by itself and in combination with digital marketing.

² This chapter is based on Lesscher, Lisan, Lara Lobschat and Peter C. Verhoef (2020), “Do Offline and Online go Hand in Hand? Cross-Channel and Synergy Effects of Direct Mailing and Display Advertising,” *International Journal of Research in Marketing*, forthcoming.

³ An earlier version of this paper is included in the MSI Working Paper Series: Lesscher, Lisan, Lara Lobschat, and Peter C. Verhoef (2020), “Do Offline and Online Go Hand in Hand? Cross-channel and Synergy Effects of Direct Mailing and Display Advertising” MSI Working Paper Series 2020, Boston, MA. Available at: <https://www.msi.org/working-papers/do-offline-and-online-go-hand-in-hand-cross-channel-and-synergy-effects-of-direct-mailing-and-display-advertising/>.

2.1. Introduction

The rise of digital media and the concomitant shifts in consumer spending have strongly influenced both marketing communications and consumer behavior. Yet direct mailing as a marketing instrument continues to remain prominent (*Forbes*, 2017) and is widely applied in practice, such that 146.4 billion pieces of (direct) mail were received by U.S. households in 2018 (Statistica, 2019). Such frequent usage mainly is due to the ability of direct mails to be mentally processed easier than emails (Millward Brown, 2009) and to generate greater brand recall (UK Royal Mail, 2015) as well as higher response rates compared to digital marketing communication (e.g., e-mail, paid search, online display, social media; ANA, 2018). Although the strengths of direct mailing thus might even be superior to those of other marketing actions and direct mails have been shown to impact consumers' purchase behavior (Kumar and Reinartz, 2016; Kim and Kumar, 2018), research into the cross-channel, i.e., offline-to-online, and synergy effects of direct mailing is scant. The UK Royal Mail (2014) hints at potential cross-channel effects of direct mailing, noting that consumers can be driven to different online activities (e.g., visiting the firm's website or engaging in social media) by a direct mail. Additionally, in a recent study by the United States Postal Service (2020), 68% of marketing managers indicated an increase in website visits after combining direct mails with digital marketing, in line with a synergy effect. The key questions then are how direct mails affect different online consumer activity metrics and how they interact with other frequently applied (digital) marketing actions. Our aim is, therefore, twofold: firstly, investigating the effectiveness of direct mailing in the online environment (i.e., cross-channel effects) and secondly, explore whether there is synergy between direct mailing and a digital marketing communication tool, i.e., display advertising.

In line with prior research, we acknowledge that direct mails can have direct effects on sales as well as indirect effects by inducing consumer activities which ultimately can lead to a

purchase (see e.g., Naik and Peters, 2009). This notion of consumers moving through different preliminary stages before eventually conducting a purchase is also called the search-purchase funnel⁴ (Verhoef et al., 2017). In line with Gopalakrishnan and Park (2019), we focus on the purchase funnel consisting of the upper (i.e., awareness and search), middle (i.e., consideration) and lower (i.e., purchase) funnel stages. Hence, beyond insights into its lower-funnel sales effects, a better understanding of the effects of direct mailing alone and in the interplay with digital marketing communication on different upper- and middle-funnel (online) performance metrics (i.e., number of (organic) online searches with generic and branded keywords and clicks on sponsored search ads) on the aggregate level is required (Srinivasan, Rutz, and Pauwels, 2016).

Furthermore, we acknowledge that firms do not use a single medium to communicate their brand message (e.g., *AdNews*, 2017) and hence have to manage multiple different marketing media simultaneously (e.g., De Haan, Wiesel, and Pauwels, 2016). In a recent study, Mark et al. (2019) provide evidence that the use of catalogues and emails together yields positive profitability for most customer segments. The effect of using multiple marketing media in combination, beyond the sum of their individual effects, can be termed media synergy (Schultz, Block, and Raman, 2012). Current literature largely neglects the synergy (i.e., interaction) effects between different types of marketing communications, particularly between direct mailing and digital marketing communication. However, these synergy effects should be taken into account when determining the actual effectiveness of specific marketing media, in our case direct mailing. This is also suggested by cross media studies by Kantar Millward Brown which identify that globally 25% of media effectiveness can be assigned to media synergies (see e.g., *AdNews*, 2017). A notable exception is the study by Zantedeschi, Feit, and Bradlow (2017) which reveals a considerable interaction effect of using catalogues and emails together.

⁴ In the following, we will use the simpler term “purchase funnel”.

Nevertheless, given that catalogues and emails are both considered different forms of direct marketing (communication) for which prior research provides evidence for direct sales effects, further insights into whether there is synergy between direct mailing and display advertising – a marketing communication option which is known to affect consumers rather in the earlier stages of the purchase funnel (e.g., Lobschat, Osinga, and Reinartz, 2017) – are needed.

To address our research questions, we conduct two experimental studies. With the first study, we aim to investigate how direct mails affect consumer activity metrics, both online and offline, in the different stages of the purchase funnel over time by analyzing quasi-experimental data from a large European insurance firm. We find that direct mails affect consumers in all stages of the purchase funnel, in accordance with a cross-channel effect of direct mailing on online consumer activity metrics on the zip-code level. In particular, direct mailing yields a lift in the number of online searches for generic keywords as well as in the number of purchases. Direct mailing negatively impacts the number of online searches for the focal firm's branded keywords and the number of clicks on sponsored search ads. Overall, direct mailing seems to positively influence consumer activity in upper funnel stages by putting the general topic of the direct mail at the top of consumers' minds. We also find support for a positive indirect sales effect of direct mailing through consumers' search and subsequent clicking activity in the online environment. Taken together, the total effect (including the direct and indirect effects) of direct mailing on purchase behavior is positive. In study 2, we find evidence for a synergy effect between direct mailing and display advertising suggesting that these marketing communication tools complement one another and when used jointly, even exceed their individual effects. In sum, our findings support direct mailing as an effective tool to positively influence consumer activity metrics throughout the purchase funnel. These effects also establish in the online environment and in combination with other digital marketing tools.

By addressing our research questions, we aim to contribute to both theory and practice. We build on research regarding direct marketing (e.g., Danaher and Dagger, 2013; Naik and Peters, 2009) and attribution modeling (e.g., De Haan, Wiesel, and Pauwels, 2016), and offer several contributions (see table 2.1).

First, we provide insights into the effectiveness of an offline marketing communication tool. Current attribution studies strongly focus on digital marketing efforts leaving offline marketing instruments widely neglected (e.g., Li and Kannan, 2014). Digitalization trends have encouraged this focus on digital marketing channels, yet many massive advertisers (e.g., Procter & Gamble, Unilever) continue to reevaluate their marketing spending and have cut digital advertising spending, which even increased their media reach (*AdWeek*, 2018). Hence, firms need to manage and allocate their marketing budgets strategically across both online and offline media (De Haan, Wiesel, and Pauwels, 2016), so insights into the effectiveness of offline marketing instruments are also of strong practical interest.

Second, we study the cross-channel, i.e., offline-to-online, effects of direct mailing and also take the indirect path into consideration. With the rise of digital media and the prevalence of studies on digital marketing channels, knowledge about the effectiveness of direct mailing (and in general offline marketing actions) on upper and middle funnel performance metrics is limited (cf. Dinner, Van Heerde, and Neslin, 2014). With a sole focus on purchase outcomes, one might miss the supporting effect of marketing activities which have led (up) to this purchase (see e.g., Srinivasan, Rutz, and Pauwels, 2016). Hence, to capture the complete effect of marketing activities, their indirect effects should also be considered.

Third, we show synergy between direct mailing and digital advertising. Current literature largely neglects the interaction of multiple marketing actions, in particular online and offline marketing efforts, although research suggest that using both in combination is best due to possible synergy effects (e.g., Danaher and Dagger, 2013).

Lastly, we contribute by investigating how direct mailing affects consumers in the different stages of the purchase funnel over a considerably long period of time. In current direct mailing and attribution studies, dynamic time effects are largely neglected, preventing any sense of whether the effects might wear out over time or continue to have a long-run impact (Kannan, Reinartz, and Verhoef, 2016). Our extended timeline is also critical for direct mails because consumers respond through multiple steps, including opening the mail, keeping it, and responding to it (Feld et al., 2013).

Table 2.1: Contributions relative to key prior research on direct marketing

Paper	Cross-channel Effects	Dynamic Time Effects	Synergy with Display Advertising
Naik and Peters (2009)	✓ (online ↔ offline)	(✓)	
Gázquez-Abad, De Cannière, Martínez-López (2011)		✓	
Pauwels et al. (2016)		(✓)	
Valenti et al. (2018)	✓ (offline → online)	(✓)	
Mark et al. (2019)	✓ (offline ↔ online)	✓	
Zantedeschi, Feit, and Bradlow (2017)	✓ (offline → online)	✓	
<i>This paper</i>	✓ (offline → online)	✓	✓

In the next section, we present our conceptual framework, review relevant studies pertaining to the purchase funnel and the (cross-channel and synergy) effects of direct mailing, and formulate our expectations. Then, we describe the unique data from both our studies and develop our models to answer our research questions. Thereafter, we present the empirical results of our analyses of both studies and conclude with implications for research and practice.

2.2. Conceptual framework

In line with Gopalakrishnan and Park (2019), we focus on the purchase funnel where the upper funnel stage refers to the share of consumers who become aware of their need and are induced to search for a product or service (i.e., awareness and search stage). This stage is followed by the middle funnel stage in which consumers interact with ads by clicking on them and eventually visit the advertising firm's website (i.e., consideration stage) (e.g., De Haan, Wiesel, and Pauwels, 2016). Lastly, in the lower funnel stage, we observe whether a certain group of consumers decides to conduct a purchase or not. For both studies, we focus on different consumer activity metrics on the aggregate, zip-code level throughout the purchase funnel in a highly similar manner (see figure 2.1).

In study 1, we analyze the potential effects of direct mailing on the different funnel stages: (1) the number of (organic) online searches (both branded and generic), which functions as a proxy for the awareness and search stage, because it is a channel to search for information (Li and Kannan, 2014); (2) the amount of clicks on sponsored search ads as a proxy for the consideration stage, because clicks lead consumers to visit the firm's website (Mulpuru et al., 2011); and (3) the number of purchases to represent the purchase stage. Beyond the effect of direct mailing on the different stages of the purchase funnel, we also investigate the relations among the different stages, i.e., (4) search $\rightarrow$ visit and (5) visit $\rightarrow$ purchase, allowing us to uncover the indirect effects of direct mailing on sales (Pauwels, Aksehirli, and Lackman, 2016). The conceptual framework in figure 2.1 details our study process.

In study 2, we aim to provide further evidence for the causal sales effect of direct mailing by analyzing its sales effect using field experiment data and diff-in-diff analyses to establish causality. Furthermore, we explore whether there is synergy between direct mailing and display advertising by investigating the change in purchase behavior when combining both types of marketing communication (6).

Figure 2.1: Conceptual Framework

2.3. Research background

Prior literature establishes that the effectiveness of a firm's digital (e.g., email marketing, display advertising) and offline (e.g., TV and print advertising) marketing communication efforts differ across the different stages of the purchase funnel (Abhishek, Fader, and Hosanagar, 2012; Pauwels, Aksehirli, and Lackman, 2016). De Haan, Wiesel, and Pauwels (2016) suggest that firm-initiated communication (e.g., e-mail, TV advertising) can reach consumers unaware of their need for the product (or category). Abhishek, Fader, and Hosanagar (2012) concur and show that firm-initiated online communication is usually most effective in the upper part of the purchase funnel, moving consumers from a disengaged to an engaged state. In our conceptual framework, the stages preceding a potential purchase constitute the upper (i.e., awareness and search stage) and middle (i.e., consideration stage) part of the purchase funnel. Furthermore, prior research reports that firm-initiated communication in the upper and middle part of the purchase funnel positively contributes to an increase in purchase probability in later stages of the funnel (Li and Kannan, 2014).

2.3.1. *Effects of direct mailing in the upper and middle part of the funnel*

We adopt the definition of a direct mail proposed by Jonker, Franses, and Piersma (2002, p. 6): “an addressed, written, commercial message.” A limited number of studies point to the effectiveness of direct mailing in the upper and middle part of the purchase funnel without providing empirical evidence; they can trigger interest in a product/service and eventually lead to purchase (Roberts and Berger, 1999). Stimulating interest is another advantage of direct mails (Feld et al., 2013). Danaher and Dagger (2013) cite direct mailing as an effective tool to reach unaware consumers and make them aware, by exposing them to advertising. Naik and Peters (2009) provide empirical evidence for the effect of direct mailing in the middle funnel stage by showing that direct mails directly affect online car configuration visits, which is used as a proxy for the consideration stage. Therefore, we expect that direct mailing influences upper

and middle funnel performance metrics, but also eventually help to move consumers along the funnel to the purchase stage, in line with an indirect effect of direct mailing.

2.3.2. Effects of direct mailing in the lower part of the funnel

Direct marketing communications seek to influence buying behavior (Rust and Verhoef, 2005). Prior academic research mainly studies the direct effects of direct mailing on purchase behavior. Past studies find that direct mailing has a positive effect on purchase (e.g., Verhoef, 2003; Gázquez-Abad, De Cannière, and Martínez-López, 2011) and adoption of a new (technological) product (e.g., Prins and Verhoef, 2007; Risselada, Verhoef, and Bijmolt, 2014). In their comparison of the relative effectiveness of multiple marketing tools, Danaher and Dagger (2013) determine that direct mailing is among the seven communication instruments that significantly influence purchase outcomes (i.e., dollar sales and profits). Specifically, they identify direct marketing as the second most effective tool when considering dollar sales as the focal outcome and the most effective if profit is the focal outcome. Recently, Valenti et al. (2018) find positive effects of direct mails on purchase behavior in a retail context for prospective customers. Overall, direct mailing appears to have a strong, positive, direct effect on purchase behavior, and we include this expected effect in our framework.

2.3.3. Cross-channel effects of direct mailing

Current literature largely neglects offline-to-online effects when investigating the effectiveness of marketing communication, focusing more on the online-to-offline effects. For example, Lewis and Reiley (2014) cite an increase in offline sales for a group of consumers exposed to banner ads, though Danaher and Dagger (2013) do not find any evidence for this cross-channel effect of display advertising. Lobschat, Osinga, and Reinartz (2017) extend this research by including the effects of different online touchpoints (i.e., banner, sponsored search, and contextual advertising) on customers' online and offline (purchase) behavior. Their findings reveal an indirect effect of banner advertising on offline purchase likelihood, through

website visits, for consumers who have not visited the advertiser's website recently. Srinivasan, Rutz, and Pauwels (2016) show effects of online customer activity in paid, owned, earned, and unearned media on (aggregate) sales and their interdependencies with traditional marketing mix elements. Despite the key insights these studies offer, they focus on the effect of digital marketing communication on offline consumer responses and neglect the effects of offline communication on online behavior.

There are a few notable exceptions which study offline-to-online effects with a focus on TV advertising. Joo, Wilbur, and Zhu (2016) investigate the effect of TV advertising on online search behavior and find that TV ads for a financial services brand increase the total number of online searches as well as the number of online searches with a branded (vs. generic) keyword. In further support of an offline-to-online effect in the upper and middle part of the funnel, Fossen and Schweidel (2017) explore the impact of TV advertising on online word-of-mouth (WOM) and find a significant positive effect on WOM volume for the advertising brand. Liaukonyte, Teixeira, and Wilbur (2015) analyze the direct (and indirect) effects of TV advertising on online website transactions for five different product categories and find support for positive indirect effects of TV ads through consumers' direct visits to the advertising firm's website as well as referrals from search engines.

In sum, research suggests a positive cross-channel effect of TV advertising. However, research considering the specific cross-channel effects of direct marketing is scant. One notable exception is Naik and Peters (2009), who examine the effects of online display advertising, offline advertising, and direct mailing on online and offline consideration metrics for a car brand. They find significant cross-channel effects, such that online advertising affects the number of offline dealership visits, and direct mailing affects the number of online car configurator visits. They only consider the upper and middle funnel stages though. Mark et al. (2019) also find evidence for an offline-to-online effect by showing a positive influence of

catalogues on purchase behavior in the digital channel. Nevertheless, it is not clear whether the latter finding can be transferred to direct mailing given that catalogues contain considerably more detailed product (and/or service) information which might alleviate the need to seek for further information (and/or move through additional intermediate stages of the purchase funnel) and hence trigger direct sales effects in the online channel right away.

Hence, even given these prior research efforts, the effects of direct mailing throughout the full purchase funnel have not been taken into account. To address this gap, we study the cross-channel effects of direct mailing on upper and middle purchase funnel metrics on the zip-code level, with the prediction that these effects are notable, and also explore whether these earlier funnel outcomes also significantly impact the lower part of the funnel, i.e., help to increase sales.

2.3.4. *Synergy effects of direct mailing*

The interactions of multiple marketing actions, in particular online and offline marketing efforts, are generally neglected in current direct mailing as well as attribution modeling literature. Media synergy is “the added value of one medium as a result of the presence of another medium, causing the combined effect of media to exceed the sum of their individual effects” (Naik and Raman, 2003, p. 385). Jagpal (1981) was among the first to find empirical support for synergy in multimedia advertising by studying the synergy between print and radio advertising. Also, Naik and Raman (2003) find synergy between offline marketing actions, whereas other studies find synergy between offline marketing actions (e.g., TV or print advertising) and digital marketing actions (i.e., Internet advertising) (e.g., Chang and Thorson, 2004; Reimer, Rutz, and Pauwels, 2014). Stammerjohan et al. (2005) provide different theoretical explanations for the existence of synergy: Encoding variability theory states that if consumers are exposed to a (marketing) message in different media, encoding will result in a “stronger, clearer, more accessible information network in the brain” (p. 56). This, in turn,

fosters the recall likelihood of the respective marketing message. Additionally, selective attention theory suggests that using multiple media increases familiarity with the marketing message, but also increases the complexity of the marketing campaign (Kahneman, 1973). This combination (i.e., a familiar but complex stimuli) is shown to increase consumer attention in line with a positive synergy effect (for an elaborate discussion on the theoretical explanations for media synergy, please see Stammerjohan et al., 2005). However, only a limited number of studies exist, which consider direct mailing when looking into the synergy effects of multimedia communication. Naik and Peters (2009) consider multiple offline (e.g., print, radio, television) and online media (e.g., banner and search ads) and find synergy effects among them. Also, they consider direct mailing, but do not find synergy effects among direct mailing and online or offline media. Similarly, Danaher and Dagger (2013) also examine direct mailing and do not find synergy effects. Zantedeschi, Feit, and Bradlow (2017) find evidence for synergy between two types of direct marketing, i.e., catalogues and emails. Pauwels et al. (2016) are the first to show synergy between online paid search and direct mailing.

Despite the efforts of current studies, research into the synergy effect of direct mailing with digital marketing communication is still rather limited and yields mixed results. To address this gap, we study the synergy effects of direct mailing with display advertising.

2.4. Study 1: Cross-channel effects of direct mailing

In our first study, we aim to study how direct mailing affects consumers in the different stages of the purchase funnel. For this purpose, we analyze quasi-experimental data on the zip code level from a large insurance firm. In the following, we describe the data as well as our modeling approach and present our key findings on the effectiveness of direct mailing.

2.4.1. Data study 1

2.4.1.1. *Quasi-experimental data*

We have access to data from a large German insurance firm, which serves us adequately to answer our first main research question. The insurance firm is a well-known company that belongs to a worldwide insurance group with more than 50,000 employees in 200 countries. The firm's well-established, multichannel distribution system includes an online presence, owned agencies, and partners. In the German market, the focal firm is positioned in the middle in terms of market share (less than 4% compared to the market leader with 16%; KIVI GmbH, 2015) and (un)aided brand recall is considerably lower compared to the main players in the market, i.e., 8% (highest: 57%) and 57% (highest: 91%), respectively (YouGov Deutschland AG, 2015). For confidentiality, we cannot disclose its name. The data that this firm provided pertain to a campaign to promote car insurances, for which direct mails were sent out to potential new customers of the insurance firm. The overall campaign ran from September 7 to October 24, 2015. For this campaign, the direct mails were sent out in week 43 (i.e., October 19–24) whereas all other campaign-related activities (i.e., TV advertising, online video advertising, social media marketing) were stopped 3 weeks before (i.e., September 7–28, 2015); these ended in week 40⁵. Hence, there is a time gap of 3 weeks between all non-direct mailing campaign activities and the direct mailing campaign.

The data cover 609 German zip codes (5-digit level) and are quasi-experimental (cf. Liaukontye, Teixeira, and Wilbur, 2015), such that they reflect a treated ($n = 596$) and a control group ($n = 13$), for which only the treated group received direct mails from the insurance firm. For both groups, we have information over an 11-week period (October 24, 2015–January 03,

⁵ Previous research suggests that these marketing activities should not influence our results given that their effects do not prolong for such a long period. Guitart and Hervet (2017) study the effects of TV advertising on online conversions and find that the effects of TV ads (including for a car insurance) level out after only 15 hours. Given this, we are confident that TV advertising did not bias our results. Same holds for online video ads and the firm's social media activities (see e.g., De Haan, Wiesel, and Pauwels, 2016).

2016) on the number of generic and branded online searches on Google per zip code, the number of clicks on sponsored search ads from the focal firm per zip code, as well as the number of purchases per zip code with the relevant time stamp information included.

The selection of the treatment (and control) group reflected the households' purchase potential in a specific zip code region, based mainly on age and income, though the firm's exact algorithm is unknown. The control group comes from similar zip code regions with the same household potential that ultimately did not receive any direct mails. The insurance firm confirmed that there were no strategic considerations which have led to the zip codes in the control group not receiving direct mails. Also, the zip code regions in the control group are geographically representative of Germany, covering 7 out of the 10 main regions in Germany⁶. To further validate the control group and check for differences, we used GfK data about the purchasing power and additional data from the insurance firm on socio-demographics (i.e., share of men, share of households with 1-2 persons, share of high social status households, and share of households with the head aged 0-40 years old) of the zip code regions. T-test analyses of the difference in purchasing power, socio-demographics, and focal dependent variables in the before period of the treatment group and control group show that they do not differ significantly (see appendix 2.A for the comparisons). In sum, these results establish confidence in the composition of our experimental groups.

2.4.1.2. Variable operationalization

The unit of analysis is customer behavior at the zip code level, measured on a weekly basis. The German zip codes are on the 5-digit level, which is the most granulated level of zip code level data for Germany. With regard to the size of these zip codes, the 609 zip codes in the data have an average of 10,154 (4924) inhabitants (households), ranging from 365 (181) to 50,418 (24,081). We aggregate daily data to a weekly level because the variation per day is limited.

⁶ This also holds for the treatment group covering 10 out of the 10 main regions in Germany.

Such a weekly aggregation is relatively common for research into direct response media, due to their low response rates (e.g., Srinivasan, Rutz, and Pauwels, 2016). Consumers often take some time to respond to (direct) mails, including the steps of opening, keeping, and responding to them, so analyzing daily data seems less useful (Feld et al., 2013). The data of interest are observed consumer activity metrics linked to the focal direct mailing campaign, so we only use data collected after October 24, 2015. As a cutoff date, we use January 3, 2016, or eleven weeks after the direct mails were sent out. This period should be sufficient, because direct mails have a peak effect one month after they have been sent out (Montgomery and Silk, 1972). Moreover, the data cover the start of a new calendar year, when consumers often decide whether to switch their insurance policies or not (*Frankfurter Allgemeine Zeitung*, 2015). In the following sections, we elaborate on the operationalization of our focal variables.

2.4.1.2.1. *Direct mailing*

The direct mail we study is informational, mainly featuring information about car insurances and its relevance in general. The design was not personalized, so it was the same for all consumers, including images, a brief description of the insurance highlighted by the campaign, and the firm's logo (appendix 2.E; logo is hidden to maintain confidentiality). For the entire campaign, 450,000 direct mails were sent to potential new customers of the focal firm by a direct marketing firm, which holds an address data base of nearly 90% of all households in Germany enriched with additional information about the respective households (information provided by the direct marketing firm). Through a matching process with the focal insurance firms CRM system, the direct marketing firm was able to target potential new customers almost exclusively.

2.4.1.2.2. *Organic search behavior*

We have information about the number of online search queries in response to the campaign on the search engine of Google at the zip code level and can distinguish two search query

categories: branded and generic. Branded search queries contain our focal brand name in the list of keywords used to search (e.g., “State Farm insurance,” “Allstate car insurance”); whereas generic search queries include product-category related search queries, but exclude both the focal brand name and/or competitor brand names (e.g., “car insurance,” “how to insure my car”) (cf. Ghose and Yang, 2009). The data provider indexed the absolute query volume, so all absolute values are divided by a random base value. This indexing does not create any issues; it still allows us to see the movements and ratios between data points and thereby check the relative differences among data points. The data encompass the indexed number of generic (branded) online search queries for all zip codes over eleven weeks, which range from 0.25 to 278 (0.50 to 11), with average values of 3.07 (0.79) per zip code region⁷.

2.4.1.2.3. *Clicks on sponsored search ads*

With sponsored search advertising, the firm pays a fee to a search engine operator (e.g., Google) to display its ads, alongside the organic search results (Ghose and Yang, 2009). We have information on the number of clicks on our focal firm’s sponsored search ads that led to website visits by consumers in each zip code region. The data comprise 3,217 clicks on sponsored search ads, ranging from 0 to 18 with an average of 0.48 clicks on sponsored search ads per zip code region per week over our 11-week period.

2.4.1.2.4. *Purchase behavior*

The insurance firm records purchase behavior, including the number of purchases per zip code region, both online and offline. These data do not allow us to assign purchases of a zip code region to offline or online channels, but from additional data provided by the insurance firm, we determine that approximately 60% of total purchases take place online and 40% offline. The data cover purchase behavior from 609 zip codes, with a total number of 16,059

⁷ The inspection of the respective box plot reveals 4 extreme outliers with values for the indexed number of generic searches for a zip code in a given week exceeding 100. When excluding the corresponding zip codes from our model estimation, our focal results remain robust.

purchases, ranging from 0 to 107 with an average of 2.41 purchases per zip code region per week over our 11-week period. Of those purchases, only 302 were conducted by existing customers of the focal insurance firm, i.e., 1.87%.

2.4.1.2.5. *Missing data*

Our data come from a large quasi-experiment, including many zip code regions which we observe over a long observation period, which increases the chance for missing data. In our study, we have to deal with data, which is missing due to a technical matter on the side of the data provider. For search queries and clicks on sponsored search ads, the data contain entries if a search query or click on sponsored search ad is being conducted by a specific zip code in a certain week. However, the “no entries” can be due to (a) missing roll-up of non-attributed query or clicks data or (b) no search queries or clicks in a given week for a given zip code. We find that this data is missing at random (see appendix 2.D). Therefore, it is appropriate to treat the missing data points with multiple imputation⁸ (Schafer and Graham, 2002). Analyses with incomplete data would likely result in inaccurate and/or biased predictions. Therefore, we rely on imputation of missing data to make use of all available information in the data (Schafer, 1997). Specifically, the multiple imputation method applies available data to predict missing data points. More details on the missing data and imputation process can be found in appendix 2.D. Moreover, we tested the robustness of our results by analyzing our models with only non-missing data as well as imputing the missing values with zeros and find our results to be highly consistent. For more information, please refer to chapter 2.4.3.4. on robustness checks.

2.4.2. **Model development**

We propose a model for each funnel stage with a simultaneous system of equations for the upper funnel stage (i.e., number of generic and branded online searches) and separate equations for the middle and lower funnel stages (i.e., number of clicks on sponsored search ads and

⁸ Even if missing data are not missing at random, treating them with “multiple imputation” often produces unbiased estimates (Schafer and Graham, 2002).

number of purchases) to analyze the data. We estimate our models to show the main effects of direct mailing (i.e., main effect models), but also aim to study how these effects develop over time. For this purpose, in addition to our main effect models, we also estimate our models including a time interaction (i.e., time interaction models). We elaborate on our model development and the specific models we use in the following sections.

2.4.2.1. Model development of the main effect models

For each of the purchase funnel stage models, we are interested in showing the effects of direct mailing and the impact of the previous funnel stage while controlling for a set of additional variables. Therefore, in the following, we show how we include the treatment effect of direct mailing as well as the control variables before going into the model specifications.

2.4.2.1.1. Direct mailing

Our main interest is studying the direct and indirect effects of direct mailing throughout the purchase funnel. However, we are aware that the effects of direct mailing might level off over time (East, 2003). Therefore, we include a decay effect, by changing the treatment effect to 0 for the treatment group six(seven) weeks after the direct mails have been sent out, in line with research showing that direct mailing has peak effects one month after they have been sent out (Montgomery and Silk, 1972)⁹. We also tested our models with an ad stock to capture the decay effect of advertising over time (e.g., Risselada, Verhoef, and Bijmolt, 2014). The models with ad stock specifications (for direct mailing, industry advertising spending and consumer activities in the purchase funnel) show highly similar results compared to our focal model (for more information, please see chapter 2.4.3.4. on robustness checks). However, a comparison of model fit (also including the variables which will be discussed in 2.4.2.1.2) reveals that our proposed specification has the best model fit for most models (awareness & search stage:

⁹ A comparison of the model fit of different specifications, in which we set the effect of direct mailing to zero after 4, 5, 6, and 7 weeks (including the model without decay), reveals that the model with the treatment effect set to zero after 6 weeks had the best fit for the upper and middle stage funnel models and 7 weeks for the lower funnel model (see appendix 2.B), so we adopt this specification.

BIC(focal model) = -8242.33 < BIC(ad stock model) = 21997.12; consideration stage: BIC(focal model) = 12748.10 < BIC(ad stock model) = 15448.88; purchase stage: BIC(focal model) = 15987.63 > BIC(ad stock model) = 9829.35).

2.4.2.1.2. *Control variables*

In order to control for multiple aspects which might serve as confounds, we also include control variables in our models (see also table 2.2). First, we include lags of the dependent variables in the equations (e.g., including PurchasePrev_{it} in the purchase equation), as a general way to control for unobserved variables (Wooldridge, 2012). Besides the lagged dependent variables, we also control for socio-demographics of the zip code regions (time-invariant) as well as own and competitive marketing activities in a given week¹⁰. In order to control for own and competitive marketing activities, we include the indexed weekly total industry advertising spend in our models as well as the average rank of the sponsored search ads of the focal firm. For the weekly total industry advertising spend, we apply an ad stock specification, in line with prior research (e.g., Datta, Ailawadi, and Van Heerde, 2017). We identified the optimal carry-over parameters with a grid search (0.9 for the awareness and search stage and 0.1 for purchase stage). Lastly, we control for the number of direct mails sent to each zip code region in the treatment group¹¹. After adding the control variables to the models, we obtain our final main effect models for each purchase funnel stage.

2.4.2.2. *Upper funnel stage model*

In order to analyze the effects of direct mailing in the upper funnel stage, we propose a simultaneous system of equations model for organic search use (number of generic (equation

¹⁰Given that some socio-demographics are highly correlated, we opted to only include those socio-demographics, which are not highly correlated, in order to circumvent potential multicollinearity issues. The results of the models with and without the highly correlated socio-demographics are robust, except for the correlation between ad spending and rank of the sponsored search ads. Therefore, we present the models with all covariates in the main text. Only for the middle funnel stage model, we exclude “ad spending” in favor of “rank” as covariate. For these models, multicollinearity does not seem to pose an issue based on the VIF values (see appendix 2.I).

¹¹ For some zip code regions in the treatment group, we were not provided with the number of direct mails send. Therefore, we also analysed our models without these zip code regions and results are robust.

(1a)) and branded online searches (equation (1b)) (cf. Agarwal, Hosanagar, and Smith, 2015; Ghose and Yang, 2009). Both types of organic search use (generic and branded) compose the awareness & search stage in the funnel. With two dependent variables and their interrelation, one equation does not suffice to specify the relations and therefore, a simultaneous system of equations can be used (as indicated by Leeflang et al., 2015).

We simultaneously estimate the system of equations model for all zip code regions using three-stage least squares (3SLS) (Zellner and Theil, 1962)¹². The model is specified as follows:

$$\begin{aligned} \text{GenericSearch}_{it} = & \alpha + \delta_1 \text{DM}_{it} + \delta_2 \text{BrandedSearch}_{it} + \delta_3 \text{GenericSearch}_{it-1} + \delta_4 \text{BrandedSearch}_{it-1} \\ & + \delta_5 \text{GenericSearch}_{it-2} + \delta_6 \text{BrandedSearch}_{it-2} + \delta_7 \text{AdstockAdspend}_t + \delta_8 \text{Highstatus}_i \\ & + \delta_9 \text{Male}_i + \delta_{10} \text{Household}_{1-2i} + \delta_{11} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (1a)$$

$$\begin{aligned} \text{BrandedSearch}_{it} = & \alpha + \zeta_1 \text{DM}_{it} + \zeta_2 \text{GenericSearch}_{it} + \zeta_3 \text{GenericSearch}_{it-1} + \zeta_4 \text{Brandedsearch}_{it-1} \\ & + \zeta_5 \text{GenericSearch}_{it-2} + \zeta_6 \text{Brandedsearch}_{it-2} + \zeta_7 \text{AdstockAdspend}_t + \zeta_8 \text{From00to40}_i \\ & + \zeta_9 \text{Male}_i + \zeta_{10} \text{Household}_{1-2i} + \zeta_{11} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (1b)$$

In this system of equations, DM_{it} represents whether the zip code region i is in the treatment group (1) or in the control group (0), $\text{GenericSearch}_{it}$ is the average indexed number of generic online search queries for a zip code region i in week t , BrandSearch_{it} is the average indexed number of branded search queries for a zip code region i in week t , AdstockAdspend_t is the ad stock¹³ for the indexed total amount of advertising spending for the German insurance industry in week t , Highstatus_i represents the share of households with a high social status for zip code region i , From00to40_i represents the share of households with the household head aged 0-40 years old for zip code region i , Male_i represents the share of male inhabitants for zip code region i , Household_{1-2i} represents the share of households with a household size of 1-2 persons for zip

¹² Given the simultaneous estimation of our model and our initial analyses showing that the regressors of one or more equations are correlated with the disturbances, a 3SLS method leads to consistent and asymptotically more efficient estimates than a two-stage least squares (2SLS) method if the disturbances might be collectively correlated (Zellner and Theil, 1962). A Hausman (1978) test confirms that the 3SLS estimation is best for our models (null hypothesis accepted, $p > .05$).

¹³ $\text{AdstockAdspend}_t = \text{Adspend}_t + \delta \text{AdstockAdspend}_{t-1}$ where AdstockAdspend_t is the ad stock for advertising spend in week t , Adspend_t is the indexed total amount of advertising spending for the German insurance industry in week t , and δ is the carry-over parameter. For the first week, the ad stock is set equal to the advertising spend in that time period. We identified the optimal carry-over parameters with a grid search. For the upper funnel stage model this is 0.9 and for the lower funnel stage model 0.1.

code region i , and SendDMs_i ¹⁴ represents the number of direct mails received by a zip code region i . We exclude From00to40_i (Highstatus_i) from the generic (branded) search equation in order to tackle the problem of identification arising from estimating both search equations simultaneously, i.e., in a system of equations (Greene 2002, p. 385)¹⁵.

2.4.2.3. Middle funnel stage model

In order to analyze the effects of direct mailing in the middle funnel stage, we model the number of clicks on sponsored search ads. We estimate the middle funnel stage model for all zip code regions using ordinary least squares (OLS). The model is specified as follows:

$$\begin{aligned} \text{Clicks}_{it} = & \alpha + \eta_1 \text{DM}_{it} + \eta_2 \text{GenericSearch}_{it} + \eta_3 \text{BrandedSearch}_{it} + \eta_4 \text{GenericSearch}_{it-1} \\ & + \eta_5 \text{BrandedSearch}_{it-1} + \eta_6 \text{Clicks}_{it-1} + \eta_7 \text{GenericSearch}_{it-2} + \eta_8 \text{BrandedSearch}_{it-2} \\ & + \eta_9 \text{Clicks}_{it-2} + \eta_{10} \text{Rank}_t + \eta_{11} \text{Highstatus}_i + \eta_{12} \text{From00to40}_i + \eta_{13} \text{Male}_i \\ & + \eta_{14} \text{Household}_{1-2i} + \eta_{15} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (2)$$

In this model, we define the following additional variables: Clicks_{it} is the average number of clicks on sponsored search ads for a zip code region i in week t , and Rank_t is the average rank of the sponsored search ads for the focal firm in week t .

2.4.2.4. Lower funnel stage model

In order to analyze the effects of direct mailing in the lower funnel stage, we propose a model for the number of purchases (i.e., Purchase_{it} – the number of purchases (both online and offline) for a zip code region i in week t). We estimate the lower funnel stage model using a zero-inflated negative binomial model¹⁶ (Wooldridge, 2012; Leeflang et al., 2015). Our dependent variable (i.e., number of purchases) is a count variable with overdispersion, which requires a negative binomial distribution (Wooldridge, 2012; Leeflang et al., 2015). Moreover, we have

¹⁴ This control variable is used to control for the size of a zip code region and leads to no issues with DM (direct mailing treatment) in our models as the correlation between the variables is low (see appendix 2.I). Reasons for this might be that not all households in a zip code receive a direct mail or the relatively small control group not receiving any direct mails whereas all other zip codes receive direct mails in large numbers. When estimating our models without this control (SendDMs), results remain similar. This serves as an indication that multicollinearity does not pose a serious concern (Leeflang et al., 2015).

¹⁵ We also ran both equations separately with all covariates included and results are similar, although the treatment effect on branded search turns insignificant.

¹⁶ More information on (the selection of) this model can be found in appendix 2.K.

to account for excess zeros in our data, as there is disproportionately high number of non-purchase incidences in our data. The model is specified as follows:

$$\begin{aligned} \text{Purchase}_{it} = & \alpha + \beta_1 \text{DM}_{it} + \beta_2 \text{Clicks}_{it} + \beta_3 \text{Clicks}_{it-1} + \beta_4 \text{Clicks}_{it-2} + \beta_5 \text{PurchasePrev}_{it-1} \\ & + \beta_6 \text{PurchasePrev}_{it-2} + \beta_7 \text{PP}_i + \beta_8 \text{AdstockAdspend}_t + \beta_9 \text{Highstatus}_i + \beta_{10} \text{From00to40}_i \\ & + \beta_{11} \text{Male}_i + \beta_{12} \text{Household}_{1-2i} + \beta_{13} \text{SendDMs}_i + \epsilon_{it} \end{aligned} \quad (3)$$

In this model, we define the following additional variables: Purchase_{it} is the number of purchases (both online and offline) for a zip code region i in week t , PurchasePrev_{it} represents whether there was a purchase in the previous week(s) (1) or not (0) for a zip code region i in week t , and PP_i represents the purchasing power per household index of Germany for a zip code region i . We also used the actual count of purchases per zip code in previous weeks in our model and find our results to be similar in size and sign.

2.4.2.5. Time interaction effect models

In line with Kannan, Reinartz and Verhoef (2016) indicating the importance of understanding dynamic time effects, we concur that the effects of direct mailing might change within the first 6 weeks after the direct mails have been sent out. Therefore, we explore how the effect of direct mailing develops over time by estimating an additional model for each purchase funnel stage that explores the effects of direct mailing on the different funnel stages in more depth. Here, the main effects models (equations 1a, 1b, 2 and 3) serve as a base, and we add an interaction term for the treatment variable and an elapsed time variable, which represents the weeks since the direct mails were sent out (Konus, Neslin, and Verhoef, 2014)¹⁷. Given that the indexed total industry advertising spending variable causes potential multicollinearity issues when the time variable is included, this variable was excluded from the models. The detailed model specifications (equations C1a, C1b, C2, C3) can be found in

¹⁷ To include an appropriate time specification, we compare different models with different time specifications (i.e., elapsed time t , time t squared, square root of time t , and log of time t) for each of the funnel stage models (see appendix 2.B). This table lists the pertinent information criteria; the time t squared specification offers the most appropriate option for all purchase funnel models, so this time specification is included in all interaction models.

appendix 2.C. We estimate the time interaction models for each of the purchase funnel stages similar to the main effect models.

2.4.3. Results

Our main results are provided in tables 2.2 and 2.3 (for the full results of the interaction models, please see appendix 2.F; results are similar in sign and size). In addition to a positive sales effect, direct mailing significantly influences the upper and middle stages of the purchase funnel, in support of cross-channel effects of direct mailing on consumers' online search and clicking behavior. We will discuss our findings for each of the purchase funnel stages in the following.

2.4.3.1. Upper funnel stage

The results indicate that direct mailing leads to an increase in the number of generic online searches ($\delta_1 = 2.52, p < .001$). On the other hand, we find a negative effect of direct mailing on the number of branded online searches (for the focal firm) ($\zeta_1 = -0.77, p < .001$). We gain additional insights by analyzing how these effects of direct mailing develop over time (table 2.3). The treatment effect and the interaction of the treatment and time variable for the upper funnel stage are significant for both the number of generic and branded online searches. For generic online searches, the effect of direct mailing remains positive ($\theta_1 = 1.72, p < .001$) and the interaction between time and treatment is also positive ($\theta_3 = 0.06, p < .001$), suggesting that the positive effect of direct mailing starts up relatively small and exponentially increases over time up until week 6, when the treatment effect is assumed to have diminished. The same holds for online searches with branded keywords; the effect of direct mailing remains negative ($\lambda_1 = -0.51, p < .01$) and the interaction between time and treatment is also negative ($\lambda_3 = -0.02, p < .001$), suggesting that the negative effect of direct mailing on branded online searches decreases exponentially over time up until week 6.

Beyond these direct effects, we also want to uncover potential indirect effects of direct mailing throughout the purchase funnel. Results reveal that organic online searches with a generic or branded keyword also influence each other. In the same week, online searches for a generic keyword yield a lift in the number of branded online searches ($\zeta_2 = .31, p < .001$) and branded online searches increase the number of online searches for a generic keyword ($\delta_2 = 3.27, p < .001$). Regarding our control variables, we find that ad stock for weekly industry advertising spending and the share of male inhabitants of a zip code region have a significant influence. Results indicate that higher spending on advertising by the industry increases the number of generic online searches, whereas a higher share of male inhabitants decrease the number of generic online searches ($\delta_7 = 0.35, p < .01$; $\delta_9 = -32.88, p < .001$). For branded searches, this is the other way around with higher spending on advertising by the industry decreasing the number of branded online searches, whereas a higher share of male inhabitants increases the number of generic online searches ($\zeta_7 = -.11, p < .01$; $\zeta_9 = 10.04, p < .001$).

2.4.3.2. Middle funnel stage

The results indicate that the number of clicks on sponsored search ads for our focal firm slightly diminishes after receiving (vs. not receiving) direct mails ($\eta_1 = -0.08, p < .01$). The interaction effect model shows that the treatment and the interaction of the treatment and time variable for the middle funnel stage are not significant for clicks on sponsored search ads ($\rho_1 = 0.01, p > .10$; $\rho_3 = -0.00, p > .10$).

Concerning potential indirect effects of direct mailing on the purchase funnel stage, we show that the outcomes of the upper funnel stage significantly influences the middle funnel stage. In the same week, the number of organic online searches, generic and branded, increases the number of clicks on sponsored search ads (i.e., $\eta_2 = .05, p < .001$ and $\eta_3 = .54, p < .001$, respectively).

2.4.3.3. Lower funnel stage

The results indicate a positive effect of direct mailing on the number of purchases ($\beta_1 = 1.49$, $p < .001$). Additionally, the analysis on how this effect develops over time indicates that the treatment and the interaction of the treatment and time variable for the lower funnel stage are significant for the purchase equation ($\gamma_1 = -.16$, $p < .05$; $\gamma_3 = .02$, $p < .001$). Thereby, the results on this dynamic time effects (i.e., time interaction model) show that the treatment effect of direct mailing on the number of purchases turns negative when including time, but this effect increases exponentially over time and turns positive after week 2. For our control variables, results show a significant negative effect of ad stock for weekly industry advertising spending and the share of male inhabitants of a zip code region. Also, the number of direct mails received by a zip code region has a slightly positive influence on purchase whereas the effect of purchase power on purchase is slightly negative.

Furthermore, we find an effect of the middle funnel stage on the lower funnel stage, in support of an indirect (sales) effect of direct mailing. In the same week, the number of clicks on sponsored search ads increases the number of purchases ($\beta_2 = .07$, $p < .001$).

These results provide support for indirect effects of direct mailing through the search and visit stage of the purchase funnel¹⁸. Our results show that organic online searches significantly affect the number of clicks on sponsored search ads, which subsequently influence the number of purchases. These indirect effects are both positive and negative depending on the respective path considered (appendix 2.G contains the complete table with optional pathways and their indirect effects). In summary, however, we find the net effect of direct mailing on the purchase stage (i.e., overall effect, including direct and indirect effects) to be positive. For the effectiveness of direct mailing in terms of cost per acquisition (CPA), we were provided with

¹⁸ In line with Srinivasan, Rutz and Pauwels (2016), we also run a robustness check (also see section 2.4.3.4.) where we include the direct transition from the awareness & search stage to the purchase stage as we acknowledge not all consumers might follow the strict order of the funnel. We find that all effects remain the same (see appendix 2.H) as well as the net effect when taking into account this additional path.

the overall costs of the direct mailing campaign and the total number of purchases (during and after the direct mailing campaign). The CPA (for the number of sales which can be attributed to direct mailing) is €18.47. We were also provided with some information on the overall benefits of the focal campaign allowing us to conduct a crude calculation based on separate data including the costs and benefits of the direct mailing campaign. The ROI of the direct mailing, or the benefit per euro spent, is approximately €21. Together with the other results, this finding leads us to conclude that direct mailing serves as an effective marketing tool for generating (online) consumer responses throughout the purchase funnel.

Table 2.2: Results of the main effect models study 1

	Dependent variables					
	Generic search		Branded search		Clicks	Purchase
Intercept	11.60 (5.49)	*	-3.54 (1.67)	*	-0.87 (0.73)	8.60 (1.47) ***
Generic search			0.31 (0.01)	***	0.05 (0.00)	***
Branded search	3.27 (0.10)	***			0.54 (0.02)	***
Clicks						0.07 (0.02) ***
DM	2.52 (0.24)	***	-0.77 (0.08)	***	-0.08 (0.03)	** 1.49 (0.08) ***
Purchase Prev						0.42 (0.05) ***
Purchase Prev						0.54 (0.05) ***
Clicks lag 1 (t-1)					0.04 (0.01)	** 0.01 (0.02)
Clicks lag 2 (t-2)					0.05 (0.01)	*** 0.04 (0.02) *
Generic search lag 1 (t-1)	0.74 (0.01)	***	-0.23 (0.01)	***	-0.01 (0.00)	.
Generic search lag 2 (t-2)	-0.20 (0.02)	***	0.06 (0.01)	***	0.01 (0.00)	***
Branded search lag 1 (t-1)	0.33 (0.14)	*	-0.10 (0.04)	*	0.01 (0.02)	
Branded search lag 2 (t-2)	0.40 (0.14)	**	-0.12 (0.05)	**	-0.01 (0.02)	
Ad stock advertising spending	0.35 (0.12)	**	-0.11 (0.04)	**		-1.33 (0.09) ***
Rank					0.08 (0.11)	
Purchase Power						-0.01 (0.00) ***
SendDMs	0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)	0.00 (0.00) ***
High status	-0.00 (0.01)				0.01 (0.04)	0.00 (0.09)
From 00 to 40			0.00 (0.06)		0.23 (0.29)	-0.35 (0.56)
Male	-32.88 (9.41)	***	10.04 (2.91)	***	0.24 (1.14)	-12.49 (2.36) ***
Household of 1-2 persons	-0.28 (2.28)		0.09 (0.70)		0.53 (0.29)	. -0.39 (0.72)

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.3: Main results of the time interaction effect models study 1

	Dependent variables							
	Generic search		Branded search		Clicks		Purchase	
DM	1.72 (0.49)	***	-0.51 (0.19)	**	0.01 (0.08)		-0.16 (0.07)	*
Time	0.01 (0.00)	**	-0.00 (0.00)	**	0.00 (0.00)	.	0.00 (0.00)	***
DM * Time	0.06 (0.01)	***	-0.02 (0.01)	***	-0.00 (0.00)		0.02 (0.00)	***
Generic search			0.30 (0.02)	***	0.05 (0.00)	***		
Branded search	3.35 (0.18)	***			0.54 (0.02)	***		
Clicks							0.04 (0.01)	***

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

2.4.3.4. Robustness checks

In addition to our focal analyses, we examine whether our results are robust to different model specifications. We test our models (1) without control variables, (2) with the focal firm's indexed weekly advertising spending (instead of the indexed weekly industry advertising spending), (3) with conditioning amongst the different funnel stages, (4) with our purchase variable having a Poisson distribution, (5) with a system of equations model for upper and middle funnel stages, (6) where we only use non-missing data for the estimation, (7) where we impute missing values with zeros, (8) after matching the groups using propensity score matching, (9) with the direct path from the upper funnel level to the lower funnel level, and (10) with an ad stock specification for direct mailing, weekly industry advertising spend and all consumer activities (search, click and purchase behavior). All specifications provide directional support for our findings and most are similar in significance (see appendix 2.H). Additionally, we ran multiple diff-in-diff analyses in which we estimate four separate diff-in-diff analyses for our four focal DVs. We find our treatment effect across the different stages to be similar in size and sign, although the diff-in-diff estimators turns insignificant. We also ran our model with all stages estimated simultaneously and results are similar to a large extent. Across all robustness checks, we find that our results are robust establishing confidence in our findings.

2.4.4. Conclusion study 1

In today's digital media age, questions remain about how direct mailing affects consumer online (and offline) activity metrics throughout the purchase funnel. Therefore, we assess the impact of a direct mailing campaign on different upper, middle, and lower performance metrics, using quasi-experimental data on the zip code level from an insurance firm. The results indicate that direct mailing exerts effects on all stages of the purchase funnel. We find significant cross-channel effects on the number of online searches and clicks on sponsored search ads. Nevertheless, whereas the effect of direct mailing on the number of generic online searches is positive, it turns out to be negative for the number of branded online searches and clicks on sponsored search ads. Given that the focal firm is not one of the main players in the German car insurance market, it seems reasonable to assume that the direct mailing campaign put the general topic of car insurances on top of consumers' minds which triggered further category-specific (rather than brand-specific) search behavior (e.g., in favor of the main players in the market). This is also in line with Joo, Wilbur and Zhu (2016) who explore the effects of TV advertising for established brands on consumers' online search behavior. In the discussion section of their paper, the authors state that they would expect the category expansion effect (i.e., generic searches) of TV advertising to be more pronounced for more unknown brands, whereas they would expect a lower business stealing effect (i.e., branded searches). Additionally, it needs to be highlighted that direct mailing, brand-specific search behavior, and clicks on sponsored search ads will (mostly likely) provide the consumer with firm-provided information (owned media). Hence, it is reasonable to assume that consumers' need for brand-specific information from owned media is fulfilled with consumers rather turning to other, earned media such as comparison websites, which might explain the negative effects on consumers' branded search and clicking behavior. However, in combination with the positive

impact on the number of purchases, the results (across the different purchase funnel stages) provide evidence for a positive indirect (sales) effect of direct mailing.

We acknowledge that there potentially might be debate about the causality of our claims. Given the limitations of our data from study 1 (i.e., data sparsity issues), we are not able to properly conduct the required methodological approaches (i.e., diff-in-diff analysis) to establish causality. The field experiment in study 2 solves the data issues by having similar sized experimental groups and random assignment to the treatment and control group allowing us to execute diff-in-diff analyses. With this study we strive to confirm findings in the purchase phase of study 1 and to additionally study potential synergy effects.

2.5. Study 2: Synergy effects of direct mailing

With study 2, we thus aim to investigate whether there is synergy between direct mailing and display advertising and to establish/test causality for the effect of direct mailing on consumers' purchase behavior. This section proceeds with a description of our experimental data and the regression models we use to analyze these data. Next, we present our key findings on the effectiveness and synergy of direct mailing.

2.5.1. Data study 2

2.5.1.1. Field experiment study

The field experiment, which we conducted with the same large German insurance firm, had a 2 (direct mailing: yes/no) by 2 (display advertising: yes/no) between-subjects design. Hence, the zip code regions in our experimental groups differ in receiving direct mails and/or a budget (vs. no budget) being allocated for display advertising (see figure 2.2). The assignment of zip code regions to the treatment and control groups was randomized. Both direct mailing and display advertising were part of a campaign by the insurance firm to promote liability insurances. For this campaign, the direct mails were sent out on September 19 (i.e., week 38) and the display advertising campaign also started on this day.

Figure 2.2: Experimental set-up (Study 2)

		<i>Display Advertising</i>	
		Yes	No
<i>Direct Mailing</i>	Yes	Group 1	Group 2
	No	Group 3	Group 4

In line with study 1, the unit of analysis is customer behavior at the zip code level, measured on a weekly level. The data cover in total 50 German zip code regions randomly assigned to our experimental groups (i.e., 10 zip code regions for experimental groups 1 and 2 and 15 zip code regions for experimental groups 3 and 4). For all experimental groups, we have information over a thirty-week period (June 4, 2018–December 28, 2018), 15 weeks before the campaign and 15 weeks after the campaign, on the number of purchases per zip code. For all data, we also have the relevant time stamp information.

The selection of the zip code regions for all experimental groups reflected the households' potential for a specific zip code region, similar to study 1. As indicated, the assignment of zip code regions to the experimental groups was randomized. To check for potential differences between the experimental groups (and associated treatments of direct mailing and display advertising), we used additional data from the insurance firm on socio-demographics of the zip code regions. We conducted t-test analyses of the difference in socio-demographics and our focal dependent variable (i.e., number of purchases) in the before period of both the direct mailing and display advertising treatments (see appendix 2.A for the comparisons). We find significant differences between the experimental groups on some statistics¹⁹. In order to control

¹⁹ The sample size might have influenced our comparisons. Despite this, the assignment to the experimental groups was randomized, which “rules out other factors as causes (on average) and particularly addresses selection bias” (Blattberg, Kim and Neslin, 2009, p. 244). The treatment estimate is, therefore, an unbiased estimate of the causal effect of the treatment (Lewis and Reiley, 2014). Also, when we look into the differences in demographics and how the control vs. treatment group is composed, this would make the control group a more attractive group to target given their expected responsiveness to direct mailing based on the

for these differences, we include these variables as controls in our models, which will be explained in the model development section. In the following sections, we provide detailed information on the variable operationalizations.

2.5.1.1.1. Direct mailing

The direct mail in our field experiment is highly similar to the direct mail in study 1. It concerns an informational direct mail, mainly featuring information about the product category (i.e., liability insurances) and its relevance in general. Also, the design of the direct mail is the same for all consumers and includes images, a brief description of the insurance promoted by the campaign and the firm's logo (appendix 2.E; logo is hidden to maintain confidentiality). For the campaign, 1,800,000 direct mails were sent out.

2.5.1.1.2. Display advertising

The display advertising treatment in our campaign concerns the allocation of marketing budget (i.e., 25,000€) for display advertising to our treated zip code regions. During our observation period, the focal firm did not run any other display ad campaigns neither in the treated nor in the non-treated (i.e., control group) zip code regions. The display ads promote the campaign for liability insurances. The content is comparable to the direct mail featuring information about the product category and including the same images and the firm's logo.

2.5.1.1.3. Purchase behavior

The insurance firm records purchase behaviors, including the number of purchases per zip code region, both online and offline. The data cover purchase behavior from 50 zip codes, with a total number of 173 purchases, ranging from 0 to 7 with an average of 0.12 purchases per zip code region per week over the thirty weeks.

findings of Rust and Verhoef (2005). This provides us with more reassurance that the assignment to the experimental groups was random.

2.5.2. Model development

We propose a difference-in-difference (DiD) model to compare our experimental groups on their purchase behavior allowing us to establish causal effects. In order to analyze the DiD model, we evaluated the assumptions of DiD, which indicated no issues. The main assumption of DiD indicates that the treatment variable should be uncorrelated with the error term and thereby, the treatment is not related to another factor that affects the dependent variable (e.g., Wooldridge, 2012). This assumption is termed the parallel trend assumption and can be checked by visual inspection. When plotting the purchase variable over time for our experimental groups, we are confident that we meet this parallel trend assumption²⁰. However, we do also control for potential aspects, which might cause the groups to differ in their behavior. Next, we explore potential synergy between direct mailing and display advertising by estimating a model including both treatments (and their interaction). Before elaborating on the model development of these models, we will discuss the inclusion of our control variables.

2.5.2.1. Control variables

Our first analyses including all controls (i.e., socio-demographics on which the experimental groups differ) reveal that multicollinearity might be an issue given the high correlation between some of the controls. Therefore, we excluded the socio-demographic variables which highly correlate and which showed VIF values exceeding the critical cut-off value of 10 (Leeftang et al., 2015), which left us with the models as explained in the following sections. For these models, multicollinearity does not seem to pose an issue based on their correlations and VIF values (for more information, see the correlation and VIF tables in appendix 2.I).

2.5.2.2. Difference-in-difference model

Our difference-in-difference model represent the different group comparisons and their before and after treatment differences to reveal the effects of direct mailing and display

²⁰ The visual evidence for the parallel trend assumption can be found in appendix 2.J.

advertising on consumers' purchase behavior. Moreover, we include control variables in each of the models (i.e., lags of the consumer activities, indexed total industry advertising spending as well as socio-demographics of the zip code regions). With our model set-up taking into account the differences between the before and after treatment period and the differences between our experimental groups, we are able to analyze the causal effects of direct mailing as well as display advertising in our observation period for the purchase stage.

We estimate the difference-in-difference model for all zip code regions using a zero-inflated negative binomial model (Wooldridge, 2012; Leeflang et al., 2015)²¹. In addition, we also estimate this model with the interaction of treatment and the elapsed number of weeks after the direct mails have been sent out to test how the treatment effect develops over time. The model is specified as follows:

$$\begin{aligned} \text{Purchase}_{it} = & \alpha + \pi_1 \text{Direct Mailing}_i + \pi_2 \text{Display Advertising}_i + \pi_3 \text{Post}_t + \pi_4 \text{Direct Mailing}_i * \text{Post}_t \\ & + \pi_5 \text{Display Advertising}_i * \text{Post}_t + \pi_6 \text{Highstatus}_i + \pi_7 \text{House0105}_i + \pi_8 \text{Adspend}_t \\ & + \pi_9 \text{SendDMs}_i + \pi_{10} \text{PurchasePrev}_{it-1} + \pi_{11} \text{PurchasePrev}_{it-2} + \varepsilon_{it} \end{aligned} \quad (4)$$

In this model, we define the following (additional) variables: Direct Mailing_i represents whether the zip code region i is in the treatment group (= 1; experimental groups 1 and 2 which have received direct mails) or in the control group (= 0; experimental groups 3 and 4 which have received no direct mails). $\text{Display Advertising}_i$ represents whether the zip code region i is in the treatment group (= 1; experimental groups 1 and 3 which have received display advertising) or in the control group (= 0; experimental groups 2 and 4 which have received no display advertising). Post_t represents whether a week t is after (1) or before (0) the campaign period.

2.5.2.3. Synergy model

In order to analyze the potential synergy effects between direct mailing and display advertising, we propose a model which includes an interaction term between direct mailing and

²¹ More information on (the selection of) this model can be found in appendix 2.K.

display advertising on purchase behavior in the after-treatment period. We estimate the synergy model for all zip code regions using a zero-inflated negative binomial model²². The model is specified as follows:

$$\begin{aligned} \text{Purchase}_{it} = & \alpha + \tau_1 \text{Direct Mailing}_i + \tau_2 \text{Display Advertising}_i + \tau_3 \text{Direct Mailing}_i * \text{Display Advertising}_i \\ & + \tau_4 \text{Highstatus}_i + \tau_5 \text{From00to40}_i + \tau_6 \text{Male}_i + \tau_7 \text{Adspend}_t + \tau_8 \text{Number of households}_i \\ & + \tau_9 \text{PurchasePrev}_{it-1} + \tau_{10} \text{PurchasePrev}_{it-2} + \varepsilon_{it} \end{aligned} \quad (5)$$

In this model, we define the following additional variable: Number of households represents the number of households in a zip code region i .

2.5.3. Results

An overview of our main results is provided in tables 2.4 and 2.5. According to the difference-in-difference model, direct mailing significantly influences the number of purchases, providing causal support for our results of study 1. Furthermore, we find support for a synergy effect between direct mailing and display advertising. In the following, we discuss the results of our models²³.

2.5.3.1. Difference-in-difference model.

The results on the diff-in-diff estimators indicate that direct mailing leads to an increase in the number of purchases ($\pi_4 = 2.35$, $p < .05$). Similarly, there is a positive effect of display advertising on the number of purchases ($\pi_5 = 2.17$, $p < .01$)²⁴. We provide additional insights by analyzing how these effects develop over time. For this purpose, we also include the elapsed number of weeks after the treatment (i.e., direct mails have been sent out) as well as an interaction term with the direct mailing and display advertising treatment into equation (4),

²² More information on (the selection of) this model can be found in appendix 2.K.

²³ We are also able to analyze the effects of our control variables for all our models. Results indicate that share of high social status households has a marginal negative effect in our DID model and lagged purchase behavior (of one and two weeks before) has a significant positive effect. Similarly, the lagged purchase behavior positively influences the purchase behavior in the week after for our synergy model.

²⁴ When we take all control variables into account, the difference in purchases between the treatment and control group in the before period is (marginal) significant and negative for both marketing tools. There might be different reasons for this (e.g., customer heterogeneity), however, we have no evidence why this might be. The treatment and control group were randomly assigned among zip codes with a similar household potential. Thereby, this difference does not represent or influence the treatment effect. Also, results of models considering only one of the treatments do not show these significant differences in the before-period.

correspondingly (see e.g., Cong and Liu, 2020). To allow for potential non-linear effects, we also include the respective interaction terms with the squared term of this time trend specification. For direct mailing, we find support for an inverted U-shaped treatment effect over time. More specifically, the treatment effect of direct mailing increases until week 6 after which the effect starts declining, which is in line with previous research and our results in study 1 (Montgomery and Silk, 1972). For display advertising, we do not find evidence for a time trend (both interaction terms are n.s.).

2.5.3.2. Synergy model

The results on the synergy model (see equation (5)) indicate that the interaction effect between the direct mailing treatment and the display advertising treatment is significant and positive ($\tau_3 = 1.16, p < .05$). This result provides evidence for a synergy effect between direct mailing and display advertising. Furthermore, the sum of the estimated coefficients for direct mailing, display advertising and their interaction is positive. When calculating the actual effect sizes (given our zero-inflated negative binomial model, we have to take the exponential value of the estimates (e.g., Hilbe, 2011)), we find the following: The joint effect of direct mailing and display advertising on the number of purchases (joint effect size = 3.19) is significantly larger compared to the sum of the individual effects of direct mailing and display advertising (sum of individual effect sizes = 1.29). This positive synergy effect also translates into positive economic impact as the positive joint effect implies that the number of purchases increases when using both direct mailing and display advertising²⁵. Hence, our results suggest that direct mailing and display advertising complement each other and can be best used together as their joint effect exceeds their individual effects. Generally, direct mails have shown to be relatively more engaging when compared to digital ads (Venkatraman, Dimoka, Pavlou, and Vo, 2016). On the other hand, prior research on display advertising indicates that especially display ads—

²⁵ Unfortunately, we do not have access to profit information for study 2 and are, therefore, not able to provide profound insights into ROI statistics for direct mailing vs. display advertising.

which generally receive low levels of attention from consumers (only 12% of served display ads are looked at (Inskin, 2018))—serve as strong reminders, if consumers have recently been in touch with the advertising firm, e.g., through direct mails, which is also in line with encoding variability as well as selective attention theory. In this case, consumers are generally more responsive to display ads (Lobschat, Osinga, and Reinartz, 2017). When comparing zip code regions in our data which received direct mails and display advertising (group 1) with regions which only received display advertising (group 3), we find support for this. More specifically, for those zip code regions which received both types of media, the clickthrough rate is significantly higher ($M_{\text{display}} = 0.0038$, $M_{\text{display+direct}} = 0.0043$, $p < 0.05$). The same holds for the number of leads ($M_{\text{display}} = 1.17$, $M_{\text{display+direct}} = 3.17$, $p < 0.001$) as well as the number of online conversions triggered by display advertising ($M_{\text{display}} = 0.21$, $M_{\text{display+direct}} = 0.61$, $p < 0.01$). Combining these results, it seems reasonable to assume that consumers being confronted with a highly engaging direct mail will likely be more responsive to display advertising afterwards, in line with the synergetic effect we find.

Table 2.4: Results of diff-in-diff model study 2

	Purchase	
Intercept	0.94 (1.22)	
Direct Mailing	-1.69 (1.01)	.
Display Advertising	-2.13 (0.76)	**
Post	-2.52 (1.05)	*
High status	-0.97 (0.51)	.
House0105	0.40 (0.74)	
Ad spend	-0.29 (0.18)	
SendDMs	0.00	
Lagged purchase t-1	0.96 (0.25)	***
Lagged purchase t-2	0.53 (0.26)	*
Direct Mailing * Post	2.35 (1.03)	*
Display Advertising * Post	2.17 (0.80)	**

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.5: Results of synergy model study 2

	Purchase	
Intercept	-1.58 (4.86)	
Direct mailing	-0.37 (0.44)	
Display advertising	-0.58 (0.36)	
High status	-0.76 (0.48)	
From00to40	2.65 (3.37)	
Male	-3.00 (10.26)	
Ad spend	0.27 (0.27)	
Number of households	0.00	
Lagged purchase t-1	1.24 (0.23)	***
Lagged purchase t-2	0.27 (0.25)	
Direct mailing *	1.16	*
Display advertising	(0.47)	

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

2.5.3.3. *Robustness checks*

Apart from the estimation of our focal models, we analyze our models (1) without control variables and (2) with our purchase variable with a Poisson distribution. The results for both specifications are highly similar in direction and significance. This suggests that our results are robust and demonstrates that we can have confidence in our findings. In the following conclusion section, we will discuss the results of study 2 as well as the overall conclusions we draw from the two experimental studies.

2.6. General Discussion

In today's digital media age, questions remain how direct mailing affects consumers' online and offline activity metrics on the zip code level throughout the purchase funnel and how direct mailing interacts with digital marketing tools. To provide insights into these prevailing research questions, we conducted two studies. In the first study, we assess the impact of a direct mailing campaign on different upper, middle, and lower online and offline performance metrics, using data from an insurance firm. The results indicate that direct mailing exerts effects on all stages of the purchase funnel. We find significant cross-channel effects on consumers' online search and clicking behavior which – in combination with the positive impact on the number of purchases we find – provide evidence for an indirect (sales) effect of direct mailing.

The second study investigates the synergy effect of direct mailing and display advertising, using data from a follow-up field experiment with the same insurance firm. Furthermore, we are able to gain more confidence in the results of study 1 by using field experiment data, which allows us to tackle potential causal issues of study 1, to analyze the effect of direct mailing and display advertising. The results indicate that direct mailing yields a lift in the number of purchases and this also holds for display advertising. Moreover, we find support for a synergy effect between direct mailing and display advertising. The results of both studies have implications for both research and managerial practice.

2.6.1. *Research implications*

The results validate prior research investigating the effects of direct mailing on purchase behavior (e.g., Danaher and Dagger, 2013; Verhoef, 2003). We extend these studies by investigating the cross-channel (offline → online) effects as well as the indirect effects of direct mailing on consumer activity metrics which can be used as indicators for the different stages of the purchase funnel. We show a positive impact of direct mailing on the number of generic online searches and purchases, though the impact on the number of branded online searches and clicks on sponsored search ads is negative.

The divergent effects of direct mailing on the number of online searches for generic versus branded keywords suggest that direct mailing mainly influences consumers in the very early stage of their purchase funnel. As suggested by prior research (e.g., Andrews, Li, and Balocco, 2019; Agarwal, Hosanagar, and Smith, 2015), consumer search behavior becomes more focused when moving along the funnel, which implies that at the beginning of their funnel, consumers search for more generic keywords whereas more specific keywords are used further down the funnel. Thereby, generic keywords imply that consumers are higher up the funnel (i.e., upper level) and specific (branded) keywords indicate that consumers are at a lower level in the funnel. This result also aligns with Valenti et al.'s (2018) finding that direct mailing is effective only for prospective customers, in the earliest stages of their information search.

The negative effect of direct mailing on the number of branded online searches next to the positive effect on the number of generic online searches might be explained by the design and content of the direct mail with a focus on the product category over the focal brand. This negative effect thus might reflect a change in consumers' search behavior. Consumers in the treatment group use more generic keywords for their online searches, at the expense of branded keywords, relative to the control group. Their focus, after receiving the direct mail, seems to turn away from the specific brand and toward the product category in general (Ghose and Todri,

2016) especially for a firm, which is not a main player in the market and has a relatively lower brand awareness. That is, direct mails might trigger consumers to reconsider their (prior) brand choices and potentially switch to another brand. This is also in line with Joo, Wilbur, and Zhu (2016), who expect a more pronounced category expansion effect (i.e., generic searches) and a lesser business stealing effect (i.e., branded search) for TV advertising on consumers' online search behavior for unknown (vs. more known) brands. On the other hand, the negative effects of direct mailing on consumers' branded search and clicking behavior might also be explained by the direct mail already fulfilling consumers' needs for brand-specific information from owned media.

In addition, by studying how the effects of direct mailing develop over time, we specify that their positive (negative) effects on the number of generic (branded) online searches increase over time, whereas the positive effect on the number of purchases only appears with some delay, i.e., 2 weeks after the direct mails have been sent out. In line with previous research on offline marketing communications (i.e., catalogues; Mark et al., 2019), it appears that consumers first put aside the direct mail, but after some time, they reconsider and start responding (Feld et al., 2013). These results may be partially explained by the end-of-the-year effect present in the German insurance market; insurance becomes increasingly relevant for consumers, who must choose before the end of the calendar year whether they will switch or not (*Frankfurter Allgemeine Zeitung*, 2015). Thus, they face time pressures to start thinking about their car insurance so that they can make an informed decision before the new year starts, or else wait another entire year to be able to switch insurances.

We also explore the indirect sales effects of direct mailing by assessing the relationships between the different stages of the purchase funnel. Overall, we find a positive net effect of direct mailing on the purchase stage (i.e., overall effect, including direct and indirect sales effects). This is also confirmed by a positive ROI. In sum, our results indicate that direct mailing

is not only an effective marketing tool to yield direct sales effects, but also helps to positively influence consumers' progression through the purchase funnel, in support of an indirect sales effect.

Furthermore, we extend current research by exploring the synergy effect between direct mailing and display advertising. In practice, digital and traditional (offline) marketing communication tools are utilized frequently together (e.g., De Haan, Wiesel, and Pauwels, 2016; *AdNews*, 2017) and prior research suggests that using multiple marketing communication tools jointly is better than using a single marketing communication tool due to potential synergy effects (Danaher and Dagger, 2013). However, research also shows negative synergies between different types of advertising (see e.g., Bayer et al., 2020). We do have to note that this concerns different types of advertising, whereas we consider (display) advertising in combination with direct marketing, which complement each other like we discuss in the results section 2.5.3.2. As one of the first studies, we find evidence for a significant positive synergy effect of direct mailing and display advertising, which implies the combined effect of direct mailing and display advertising is larger compared to the sum of the individual effects.

2.6.2. *Managerial implications*

Our results have important implications for firms that currently use or are planning to use direct mailing. In our empirical application, we find that direct mailing effectively generates online consumer responses throughout the purchase funnel, confirming that this traditional marketing tool remains effective even in the digital media environment; it is “far from dead” (*Forbes*, 2017). In the financial services industry, which represent the heaviest users of direct mailing (DMA, 2018), firms can benefit from this tactic. Even one of the largest online companies in the world, Google, uses direct mailing to contact its (potential) B-to-B customers, despite all online opportunities to do so (CMO, 2017). Our results provide supportive evidence

that direct mails are still a viable marketing tool, given their direct and indirect impact on consumers' purchase behavior and synergy with display advertising.

Attribution modeling. Firms can also use our research to assign value to direct mailing beyond just looking at the last action, i.e., conducting a purchase in our case. Our results reveal that direct mailing also impacts the upper and middle funnel stages of the purchase funnel. Hence, by solely looking at the number of purchases as the only key performance indicator of a direct mailing campaign, marketing managers might underestimate its effectiveness. Also, as our results show, these upper and middle funnel effects eventually lead up to a positive, indirect sales effect of direct mailing. Given the relatively high investments associated with running a direct marketing campaign, marketing managers should consider also using upper and middle funnel (online) performance metrics (and the indirect effect associated with guiding consumers through the purchase funnel) to justify their direct mailing budgets to senior managers and the CEO. By using online metrics (like e.g., the number of clicks on sponsored search ads) also for their offline marketing activities, marketing managers could gain further insights into the relative effectiveness and interplay of their online and offline marketing activities. Overall, these insights can be used as information for a more efficient budget allocation across all marketing instruments.

Managing a direct mailing campaign over time. Our results show that the effects of direct mailing in the upper and lower funnel stages change considerably over time, i.e., in the 6 weeks after the direct mailing is sent out. Most prevailing is that the positive direct sales effect of direct mailing only shows 2 weeks after the direct mailing has been sent out. Given that our focal product is consultation-intensive, marketing managers should consider allocating sufficient support staff to these promising periods to the online channel, e.g., in the form of online chat personnel, and inform their agencies accordingly. Maybe marketing managers could

also consider supporting consumers' decision making for the focal brand by running e.g., TV ads (or the alike) during these time periods²⁶.

Integration of other (digital) marketing activities. Our finding in study 1 of a negative effect of direct mailing on the number of branded online searches combined with the positive effect on the number of generic online searches suggests that the specific design of the direct mail managed to put the product category top-of-mind of consumers, but not the focal brand. Hence, managers should reconsider the actual set-up of the mail and integrate the brand more prominently to avoid that consumers start to look for alternative offers. Moreover, they could also integrate a QR code (or the alike) to the focal firm's website to circumvent consumers to go to a search engine and provide easier access to the focal firm's online offering (visit stage) (United States Postal Service, 2020).

One of our findings is a positive synergy between direct mailing and display advertising. Hence, marketing managers could contemplate using direct mails in combination with digital marketing instruments. Notably, only using one of the marketing communication channels results in a smaller effect. When integrating marketing activities, the synergies between different marketing media should carefully be considered to gain the most. Overall, when planning a direct mailing campaign, marketing managers should consider how to effectively integrate other online marketing activities.

2.6.3. *Limitations and further research*

We acknowledge some limitations of our studies that also provide interesting research opportunities. In particular, though we find that direct mailing significantly affects important consumer activity metrics on the zip code level which are indicative of the different stages of the purchase funnel in our first study, our control group is relatively small. Hutchins et al. (2015) show that effect sizes are equivalent regardless the size of the control group, but our

²⁶ Please remember that the focal firm did run TV ads, but by the time the direct mails were send out, all other (supporting) marketing activities had already stopped more than 3 weeks ago.

results still might have been influenced by the control group size; Coe (2002) suggests that the control group size can influence estimates of effect sizes. Further research should account for this potential influence by using a larger control group to establish more robust results.

Another avenue for research will be to study possible differences among various types of consumers, according to their demographic information and distinct consumer responses. In both studies, the data do not allow us to distinguish individual consumers by their demographic information. Furthermore, future research could look into long-term effects of direct mails, such as customer retention, cross-buying behavior or CLV (Kumar and Reinartz, 2016; Kannan, Reinartz, and Verhoef, 2016). Also, with access to individual-level data, future research could provide more profound information on the underlying process for the synergetic effect of direct mailing and display advertising and rule out potential alternative explanation for the observed lift in sales.

Additionally, unlike prior research which mainly focusses on factors (such as the rank of a sponsored search ad in Google) that influence the effectiveness of a sponsored search ad (e.g., Ghose and Yang, 2009), we focus on exploring how direct mails impact consumers in different stages of the purchase funnel. We do not have access to any sponsored search ad characteristics and our data does not allow to differentiate the total weekly number of clicks on sponsored search ads by keyword. Thereby, we are not able to explore the effectiveness of specific sponsored search ads. We encourage future research on this aspect. We also recommend future research to separate the effects of online and offline purchases and to distinguish existing from new customers. Unfortunately, we are not able to include this in our studies as we do not have access to the required data.

Finally, both studies refer to a single, financial services firm. Though the financial service industry is studied frequently (e.g., Guitart and Hervet 2017; Verhoef 2003) and is important for Western economies, we acknowledge that other industries also use direct mails (e.g.,

retailing) and rely on their effects on purchase behaviors (Valenti et al., 2018). One main difference between the industry under study and other industries is the fact that our industry works with annual contracts that consumers potentially renew and change only once a year. Insurance products are infrequently purchased by consumers and as a consequence changes in their purchase behavior are not observed as frequently (Verhoef and Donkers, 2001), while relative high switching costs make switching behavior also not very common Verhoef (2003). Together, this can have limited the variance in the investigated consumer responses throughout the purchase funnel. Therefore, we expect that the effects of direct mails might be even stronger in other industries without these binding contracts and with more frequent purchases. Our study could be generalized in other industries.

Appendix 2.A: Statistics comparing our experimental groups

Table 2.A.1: Comparison experimental groups study 1

Statistic	Mean Control Group	Mean Treatment Group	P-value
Purchase power	106.47	111.51	.18
Share of men	.50	.50	.58
Share of households with 1-2 persons	.17	.30	.15
Share of inhabitants aged 0-40 years old	.23	.24	.11
Share of high-status households	.72	.71	.28
Generic searches before period*	1.10	1.17	.91
Branded searches before period*	.15	.17	.84
Clicks on sponsored search ads before period*	.27	.25	.92
Purchase behavior before period**	1	1	.90

* The week before the overall campaign starts (i.e., week 36, August 31-September 6, 2015). We also ran t-tests where we compare the treatment and the control group in the period (average mean across weeks) before the overall (direct mailing) campaign starts and find no evidence for significant differences between the two groups

** The week before the direct mailing campaign starts. We only have access to the number of purchases starting from the day the overall campaign starts (i.e., September 7, 2015).

Note: We acknowledge that resulting insignificances may be due to low sample size.

Table 2.A.2: Comparison experimental groups study 2

	Statistic	Mean Control Group	Mean Treatment Group	P-value
Direct Mailing treatment	Share of men	.49	.49	.26
	Share of households with house for 1 to 5 persons	.93	.48	< .001
	Share of inhabitants aged 0-40 years old	.22	.33	< .001
	Share of high-status households	.33	.23	< .001
	Purchase behavior before period*	.07	.30	> .10
Display Advertising treatment	Share of men	.49	.50	< .001
	Share of households with house for 1 to 5 persons	.72	.77	< .01
	Share of inhabitants aged 0-40 years old	.27	.25	< .001
	Share of high-status households	.30	.28	.25
	Purchase behavior before period*	.29	.04	< .05

* The week before the overall campaign starts (i.e., week 37 2018).

Appendix 2.B: Model fit comparison for model specifications

Model	Measure of fit Upper stage funnel	Measure of fit Middle stage funnel	Measure of fit Lower stage funnel
No decay	AIC = 4146.65 BIC = 4255.24	AIC = 13619.21 BIC = 13691.84	AIC = 12562.61 BIC = 12681.46
DM = 0 after week 4	AIC = 3674.90 BIC = 3783.49	AIC = 13617.27 BIC = 13689.90	AIC = 12558.80 BIC = 12677.65
DM = 0 after week 5	AIC = -1657.50 BIC = -1548.91	AIC = 13612.56 BIC = 13685.19	AIC = 12557.29 BIC = 12676.14
DM = 0 after week 6	AIC = -10568.38 BIC = -10459.80	AIC = 13608.45 BIC = 13681.07	AIC = 12544.92 BIC = 12663.76
DM = 0 after week 7	AIC = -6725.98 BIC = -6617.39	AIC = 13616.66 BIC = 13689.28	AIC = 12393.19 BIC = 12512.03

Table 2.B.1: Comparison of model fit to include decay

Notes: AIC = Akaike information criterion, BIC = Bayesian information criterion.

Model	Measure of fit Upper stage funnel	Measure of fit Middle stage funnel	Measure of fit Lower stage funnel
Elapsed time	AIC = -6485.41 BIC = -6303.44	AIC = 12369.19 BIC = 12492.65	AIC = 10755.06 BIC = 10950.06
Time squared	AIC = -6919.68 BIC = -6734.71	AIC = 12369.10 BIC = 12492.59	AIC = 10734.18 BIC = 10929.18
Square root of time	AIC = -6254.34 BIC = -6072.37	AIC = 12369.20 BIC = 12492.69	AIC = 10765.98 BIC = 10960.97
Log of time	AIC = -6013.84 BIC = -5831.87	AIC = 12369.25 BIC = 12492.74	AIC = 10776.79 BIC = 10971.78

Table 2.B.2: Comparison of model fit for time specifications

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion.

Appendix 2.C: Model specifications time interaction model

Upper funnel stage model:

$$\begin{aligned} \text{GenericSearch}_{it} = & \alpha + \theta_1 \text{DM}_{it} + \theta_2 (t^2) + \theta_3 \text{DM}_{it} * (t^2) + \theta_4 \text{BrandedSearch}_{it} + \theta_5 \text{GenericSearch}_{it-1} \\ & + \theta_6 \text{BrandedSearch}_{it-1} + \theta_7 \text{GenericSearch}_{it-2} + \theta_8 \text{BrandedSearch}_{it-2} + \theta_9 \text{Highstatus}_i \\ & + \theta_{10} \text{Male}_i + \theta_{11} \text{Household1}_{2i} + \theta_{12} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (\text{C1a})$$

$$\begin{aligned} \text{BrandedSearch}_{it} = & \alpha + \lambda_1 \text{DM}_{it} + \lambda_2 (t^2) + \lambda_3 \text{DM}_{it} * (t^2) + \lambda_4 \text{GenericSearch}_{it} + \lambda_5 \text{GenericSearch}_{it-1} \\ & + \lambda_6 \text{Brandedsearch}_{it-1} + \lambda_7 \text{GenericSearch}_{it-2} + \lambda_8 \text{Brandedsearch}_{it-2} + \lambda_9 \text{From00to40}_i \\ & + \lambda_{10} \text{Male}_i + \lambda_{11} \text{Household1}_{2i} + \lambda_{12} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (\text{C1b})$$

Middle funnel stage model:

$$\begin{aligned} \text{Clicks}_{it} = & \alpha + \rho_1 \text{DM}_{it} + \rho_2 (t^2) + \rho_3 \text{DM}_{it} * (t^2) + \rho_4 \text{GenericSearch}_{it} + \rho_5 \text{BrandedSearch}_{it} + \rho_6 \text{PP}_i \\ & + \rho_7 \text{GenericSearch}_{it-1} + \rho_8 \text{BrandedSearch}_{it-1} + \rho_9 \text{Clicks}_{it-1} + \rho_{10} \text{GenericSearch}_{it-2} \\ & + \rho_{11} \text{BrandedSearch}_{it-2} + \rho_{12} \text{Clicks}_{it-2} + \rho_{13} \text{Rank}_t + \rho_{14} \text{Highstatus}_i + \rho_{15} \text{From00to40}_i \\ & + \rho_{16} \text{Male}_i + \rho_{17} \text{Household1}_{2i} + \rho_{18} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (\text{C2})$$

Lower funnel stage model:

$$\begin{aligned} \text{Purchase}_{it} = & \alpha + \gamma_1 \text{DM}_{it} + \gamma_2 (t^2) + \gamma_3 \text{DM}_{it} * (t^2) + \gamma_4 \text{Clicks}_{it} + \gamma_5 \text{Clicks}_{it-1} + \gamma_6 \text{Clicks}_{it-2} \\ & + \gamma_7 \text{PurchasePrev}_{it-1} + \gamma_8 \text{PurchasePrev}_{it-2} + \gamma_9 \text{PP}_i + \gamma_{10} \text{From00to40}_i \\ & + \gamma_{11} \text{Male}_i + \gamma_{12} \text{SendDMs}_i + \varepsilon_{it} \end{aligned} \quad (\text{C3})$$

Appendix 2.D: Missing data and imputation method

The missing data points in our data set concern (1) the number of generic and branded searches as well as (2) the number of clicks on sponsored search ads for some weeks for some of the zip codes in our (quasi)experimental study. In total, 24,934 observations across all zip code areas, over the 11-week observation period, and for all variables are missing. The amount of missing data per variable also differs with branded search query use being the variable with most missing observations (5,848 missing observations). The reason why there is missing data is simply a technical matter on the side of the data provide. The information we were provided on the missing data issue is as follows: (1) For search queries, we only have entries in our data if a search query is being conducted by a specific zip code in a certain week. However, the “no entries” can be due to (a) missing roll-up of non-attributed query data or (b) no search queries in a given week for a given zip code. The latter also holds true for the number of clicks on sponsored search ads for a given zip code.

We carefully studied the missing data points in our data set and found that they were missing at random; the probability of missing values relates not to the values themselves but instead likely depends on variables available in the data. In our data, the missing values seem to depend on zip codes, which were not all available to link to the responses in some weeks. Therefore, it is appropriate to treat these missing data points (Schafer and Graham 2002). Analyses with incomplete data instead risks inaccurate or biased predictions. Moreover, it is better to use a dataset by imputing the missing values and treat these imputed values as real measurements than excluding subjects with incomplete data (e.g., Harrell 2015). Therefore, we imputed the missing values using a multiple imputation method. This method is also the preferred method for handling missing data (when not MCAR) (Jensen, Joy and Jensen 2008). Multiple imputation has the goal of accounting for the relationship between the unobserved and observed variables, while also taking into account the uncertainty of the imputation (e.g., Horton et al.

2012). For multiple imputation, there are different (but similar) methods. For our paper, we made use of predictive mean matching (pmm) (Little 1988). This multiple imputation method uses random draws from the conditional distribution of the target variable given the other variables (Horton et al. 2012). Next, the predictive mean matching approach imputes the observed value of the variable with missing data points that is closest in these draws, which ensures that the imputed values are plausible (Horton and Lipsitz 2001). Moreover, a random residual is added to this imputes for the missing values in order to grant the same conditional variance as the original variable. For our imputation, we made use of the MICE package in R and imputed our missing values using the dataset including all funnel stage consumer responses, instrumental variables, zip codes, weeks and treatment variables.

Appendix 2.E: Design of the Direct mailing for both studies

Study 1

Diebstahl? Marderbiss? Umweltschäden?

Mit einer riesigen Pudelmütze wäre Ihr Pkw bestens geschützt. Zumindest während er parkt. Damit aber auch alle anderen Risiken umfangreich und individuell abgedeckt sind, brauchen Sie eine Kfz-Versicherung, die genau zu Ihren speziellen Bedürfnissen passt.

Kfz-Versicherung:

- Umfassender Haftpflicht- und Kaskoschutz
- Zwei Tarifvarianten: Basis und Top
- Individuelle Zusatzbausteine und Extra-Services

Generalagentur Peter Mustermann
Musterstr. 12
12345 Musterstadt
Telefon: 0123 45678
peter.mustermann@

Mehr Infos unter:

• Solange der Winter reicht.

Peter Mustermann
Musterstr. 12
12345 Musterstadt

Study 2

EIN MISSGESCHICK IST SCHNELL PASSIERT.

Eine Privat-Haftpflichtversicherung ist für jeden wichtig – denn jedem kann mal ein Missgeschick passieren.

Besondere Leistungen der günstigen Privat-Haftpflichtversicherung:

- Wenn Sie geschädigt wurden und auf den Kosten sitzen bleiben, springen wir für den „Forderungsausfall“ ein.
- Helfen Sie Freunden und verursachen dabei einen Schaden, übernehmen wir die Kosten für diesen „Gefälligkeitsschaden“.
- Private Internetrisiken, wenn Sie z. B. eine virenverseuchte Datei weiterleiten und dadurch einen Schaden verursachen, sind mitversichert.
- Bei einem Verlust fremder oder dienstlicher Schlüssel erstatten wir die Kosten.

Generalagentur
Maximilian Mustermann
Bert-Belspiel-Straße 12
34567 Exempelstadt
Telefon 01234 567890-123

21.08.1001 1107

Wenn Sie künftig unsere Angebote und Informationen nicht mehr erhalten möchten, können Sie bei uns die Verwendung Ihrer Adressdaten für die Zusendung von Werbeschreiben widersprechen.

Herrn
Stefan Sonnenschein
Sonnenweg 12
12345 Sonnenhang

Appendix 2.F: Results table

Table 2.F.1: Results time interaction effect models study 1

<i>Independent variables</i>	Dependent variables							
	Generic search		Branded search		Clicks		Purchase	
Intercept	13.23 (5.32)	*	-3.95 (1.63)	*	-1.64 (0.85)	.	7.75 (0.55)	***
Generic search			0.30 (0.02)	***	0.05 (0.00)	***		
Branded search	3.35 (0.18)	***			0.54 (0.02)	***		
Clicks							0.04 (0.01)	***
Treatment	1.72 (0.51)	***	-0.51 (0.16)	**	0.01 (0.08)		-0.16 (0.07)	*
Time	0.01 (0.00)	**	-0.00 (0.00)	**	0.00 (0.00)	.	0.00 (0.00)	***
Treatment * Time	0.06 (0.01)	***	-0.02 (0.00)	***	-0.00 (0.00)		0.02 (0.00)	***
Purchase lag 1 (t-1)							0.45 (0.02)	***
Purchase lag 2 (t-2)							0.37 (0.02)	***
Clicks lag 1 (t-1)					0.04 (0.01)	**	0.01 (0.01)	
Clicks lag 2 (t-2)					0.05 (0.01)	***	0.02 (0.01)	***
Generic search lag 1 (t-1)	0.74 (0.01)	***	-0.22 (0.02)	***	-0.01 (0.00)	.		
Generic search lag 2 (t-2)	-0.20 (0.01)	***	0.06 (0.01)	***	0.01 (0.00)	***		
Branded search lag 1 (t-1)	0.32 (0.14)	*	-0.09 (0.04)	*	0.01 (0.02)			
Branded search lag 2 (t-2)	0.37 (0.14)	**	-0.11 (0.04)	*	-0.01 (0.02)			
Rank					0.34 (0.18)	.		
Purchase Power							-0.01	
# direct mails	0.00 (0.00)		-0.00 (0.00)		-0.00 (0.00)		0.00	
High status	-0.00 (0.03)				0.01 (0.04)			
From 00 to 40			-0.00 (0.13)		0.23 (0.29)			
Male	-33.57 (9.21)	***	10.02 (2.87)	***	0.23 (1.14)		-11.66 (0.62)	***
Household of 1-2 persons	-0.59 (2.24)		0.18 (0.67)		0.53 (0.29)	.	-0.96 (0.27)	***

. $p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

Appendix 2.G: Indirect effects of direct mailing on purchase behavior study 1

Table 2.G.1: Overview of indirect effects

Treatment	Mediating purchase funnel stages		DV	Effect size (main effect model)	Effect size (interaction effect model)
Direct mailing			Purchase behavior	1.49	0.02
	Clicks on sponsored search ads			-0.006	0
	Generic search	Clicks on sponsored search ads		0.009	0.0001
	Branded search	Clicks on sponsored search ads		-0.029	-0.0004
	Net effect			1.464	0.0197

Appendix 2.H: Results robustness checks

Table 2.H.1: Overview of results robustness checks study 1

	Our models		Model without socio-demographics		Model with focal firm's advertising spending		Model with conditioning	
Treatment effect Generic search	+	***	+	***	+	*	+	***
Treatment effect Branded search	-	***	-	***	-	*	-	***
Treatment effect Clicks on sponsored search ads	-	***	-	***	X		-	***
Treatment effect Purchase	+	***	+	***	+	***	+	***
	Purchase model estimated with Poisson		After using propensity score matching		System of equations – search and visit stages		Models with non-missing data	
Treatment effect Generic search	X		+	***	+	***	+	***
Treatment effect Branded search	X		-	***	-	***	-	***
Treatment effect Clicks on sponsored search ads	X		-	***	+	n.s.	+	n.s.
Treatment effect Purchase	+	***	+	***	X		+	***
	Models with zeros for missing data		Models with direct effect of upper to lower level funnel		Models with ad stock			
Treatment effect Generic search	+	n.s.	+	***	+	***		
Treatment effect Branded search	-	n.s.	-	***	+	*		
Treatment effect Clicks on sponsored search ads	-	n.s.	-	***	+	***		
Treatment effect Purchase	X		+	***	+	***		

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Appendix 2.I: Correlations and variance inflation factor (VIF) values tables

		MEAN	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Purchase	2.41	4.93	1.00 (1.00)														
2	Generic search	3.07	7.27	.12 (0.00)	1.00 (1.00)													
3	Branded search	0.79	0.70	.09 (0.00)	.46 (0.00)	1.00 (1.00)												
4	Clicks	0.48	1.07	.14 (0.00)	.53 (0.00)	.54 (0.00)	1.00 (1.00)											
5	Treatment	x	x	.01 (0.29)	.00 (0.84)	.00 (0.95)	.01 (0.63)	1.00 (1.00)										
6	IV generic search	0.61	1.41	.03 (0.06)	.62 (0.00)	.47 (0.00)	.55 (0.00)	.02 (0.24)	1.00 (1.00)									
7	IV branded search	0.61	0.20	.06 (0.00)	.44 (0.00)	.36 (0.00)	.41 (0.00)	-.06 (0.00)	.66 (0.00)	1.00 (1.00)								
8	Purchase power	111.40	17.48	-.13 (0.00)	-.14 (0.00)	-.13 (0.00)	-.13 (0.00)	.04 (0.00)	-.17 (0.00)	-.11 (0.00)	1.00 (1.00)							
9	Adspend	0.99	0.46	.10 (0.00)	.10 (0.00)	0.00 (0.97)	-.01 (0.62)	.00 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	1.00 (1.00)						
10	Rank	2.58	0.12	.10 (0.00)	.05 (0.00)	-.01 (0.31)	-.01 (0.49)	.00 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	.59 (0.00)	1.00 (1.00)					
11	High status	0.30	0.35	-.05 (0.00)	-.01 (0.57)	-.03 (0.00)	-.02 (0.11)	.05 (0.00)	.10 (0.00)	.11 (0.00)	.67 (0.00)	0.00 (1.00)	0.00 (1.00)	1.00 (1.00)				
12	From00to40	0.24	0.04	.12 (0.00)	.20 (0.00)	.14 (0.00)	.14 (0.00)	.04 (0.00)	.34 (0.00)	.23 (0.00)	-.20 (0.00)	0.00 (1.00)	0.00 (1.00)	-.04 (0.00)	1.00 (1.00)			
13	Male	0.50	0.01	-.17 (0.00)	0.00 (0.86)	.02 (0.14)	0.00 (0.83)	.02 (0.14)	.22 (0.00)	.11 (0.00)	.06 (0.00)	0.00 (1.00)	0.00 (1.00)	-.11 (0.00)	.02 (0.06)	1.00 (1.00)		
14	Household1_2	0.71	0.05	.19 (0.00)	.16 (0.00)	.13 (0.00)	.14 (0.00)	-.03 (0.01)	.22 (0.00)	.22 (0.00)	-.47 (0.00)	0.00 (1.00)	0.00 (1.00)	-.14 (0.00)	.26 (0.00)	-.41 (0.00)	1.00 (1.00)	
15	SendDMs	804.8	1042.82	.24 (0.00)	.06 (0.00)	.03 (0.03)	.04 (0.00)	.12 (0.00)	.01 (0.76)	.05 (0.02)	.01 (0.29)	0.00 (1.00)	0.00 (1.00)	.03 (0.10)	.05 (0.03)	-.22 (0.00)	.21 (0.00)	1.00 (1.00)

Table 2.I.1: Descriptive statistics and correlation study 1

		MEAN	SD	1	2	3	4	5	6	7	8	9	10
1	Purchase	.1177	.4858	1.00 (1.00)									
2	Direct Mail Treatment	x	x	.18 (0.00)	1.00 (1.00)								
3	Display Ad treatment	x	x	-.02 (0.60)	-.02 (0.65)	1.00 (1.00)							
4	High status	.4852	.3631	-.08 (0.00)	-.18 (0.00)	-.04 (0.24)	1.00 (1.00)						
5	Male	.4932	.1338	-.07 (0.00)	.04 (0.23)	.28 (0.00)	-.01 (0.59)	1.00 (1.00)					
6	House size 1-5 persons	.6811	.2575	-.18 (0.00)	-.84 (0.00)	.11 (0.00)	.11 (0.00)	.13 (0.00)	1.00 (1.00)				
7	From 00 to 40	.2852	.0660	.17 (0.00)	.83 (0.00)	-.16 (0.00)	-.06 (0.01)	-.02 (0.50)	-.91 (0.00)	1.00 (1.00)			
8	Ad spend	2.154	.6584	0.00 (0.88)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)	1.00 (1.00)		
9	Number of households	8063	5235.42	.21 (0.00)	.78 (0.00)	0.00 (0.93)	-.34 (0.00)	-.28 (0.00)	-.70 (0.00)	.61 (0.00)	0.00 (1.00)	1.00 (1.00)	
10	SendDMs	962.34	1440.75	.04 (0.07)	.84 (0.00)	.01 (0.88)	-.14 (0.00)	.05 (0.04)	-.25 (0.00)	.19 (0.00)	0.00 (1.00)	.39 (0.00)	1.00 (1.00)

Table 2.I.2: Descriptive statistics and correlation study 2

Table 2.I.3: VIF values Main effect models study 1

	Generic search	Branded search	Clicks	Purchase
Generic search	X	2.36	2.56	X
Branded search	1.21	X	1.32	X
Clicks	X	X	X	1.21
DM	1.67	1.68	1.29	5.25
Purchase Prev	X	X	X	1.20
Purchase Prev	X	X	X	1.20
Clicks lag 1 (t-1)	X	X	1.74	1.24
Clicks lag 2 (t-2)	X	X	1.77	1.21
Generic search lag 1 (t-1)	2.33	3.39	3.57	X
Generic search lag 2 (t-2)	2.37	2.35	2.63	X
Branded search lag 1 (t-1)	1.35	1.34	1.57	X
Branded search lag 2 (t-2)	1.33	1.33	1.59	X
Purchase power	X	X	X	2.60
Ad stock ad spend	1.67	1.67	X	5.32
Rank	X	X	1.28	X
SendDMs	1.08	1.08	1.08	1.18
High status	1.06	X	1.06	1.97
From 00 to 40	X	1.14	1.14	1.16
Male	1.31	1.29	1.34	1.35
Household of 1-2 persons	1.36	1.39	1.45	1.89

Table 2.I.4: VIF values Interaction effect models study 1

	Generic search	Branded search	Clicks	Purchase
Generic search	X	2.40	2.60	X
Branded search	1.21	X	1.32	X
Clicks	X	X	X	1.20
DM	7.72	8.29	9.88	9.61
Time	3.37	3.74	9.07	5.09
Purchase Prev	X	X	X	1.23
Purchase Prev	X	X	X	1.24
Clicks lag 1 (t-1)	X	X	1.74	1.23
Clicks lag 2 (t-2)	X	X	1.77	1.20
Generic search lag 1 (t-1)	2.34	3.45	3.57	X
Generic search lag 2 (t-2)	2.38	2.37	2.64	X
Branded search lag 1 (t-1)	1.35	1.35	1.58	X
Branded search lag 2 (t-2)	1.34	1.34	1.59	X
Purchase power	X	X	X	1.40
Ad stock ad spend	X	X	X	X
Rank	X	X	3.49	X
SendDMs	1.08	1.08	1.08	1.19
High status	1.06	X	1.06	X
From 00 to 40	X	1.15	1.14	X
Male	1.31	1.29	1.34	1.30
Household of 1-2 persons	1.37	1.40	1.45	1.75
DM * Time	3.98	3.98	4.18	3.61

Appendix 2.J: Difference-in-Difference assumptions

Figure 2.J.1: Visual evidence parallel trend assumption

Appendix 2.K: Zero-inflated negative binomial model

For the purchase models in our chapter (equations 3, 4 and 5), we make use of zero-inflated negative binomial models (Wooldridge, 2012; Leeflang et al., 2015). We determined this model based on two aspects: (1) the purchase variable being a count and (2) having excess zeros in our data, which we will explain in the following.

(1) Our dependent variable (i.e., number of purchases) is a count variable, which requires a Poisson distribution (Wooldridge, 2012; Leeflang et al., 2015). The Poisson distribution assumes that the mean and variance are equal, which is taken to be a shortcoming of the Poisson model (Greene, 2002) as the assumption is often violated in applications (Wooldridge, 2012; Leeflang et al., 2015). An alternative that takes into account overdispersion is the negative binomial model. When testing for over-dispersion in our purchase models (equations 3, 4 and 5), we find all tests to be significant and the dispersion parameter (which indicates how many times the variance is larger than the mean) to be larger than 1 for all our purchase models (i.e., 5.15 for purchase equation 3, 1.61 for diff-in-diff model equation 4, and 1.54 for synergy model equation 5). Hence, this provides evidence for the negative binomial (NB) model to be most suitable given the data structure, because with the NB model, the Poisson assumption that the mean equals the variance is relaxed (Greene, 2002).

(2) The zero-inflated aspect in the model is used to control for excess zeros in the consumers responses. In our data, we also have to account for excess zeros, as there is disproportionately high number of non-purchase incidences in our data. Figures 2.K.1 and 2.K.2 graphically represent the zero-inflation in our data with high peaks of zero observations in both studies. As indicated by Leeflang et al. (2015) and Hilbe (2011), a problem of the Poisson and negative binomial models, for example for purchase incidences, is that they do not integrate non-buying occasions. Both of these models predict that a

purchase occasion will occur at some point in time and expect a number of zero counts for a given value of the mean. However, in case of excess zeros (i.e., high number of zero counts), the number of zero counts is (far) higher than the negative binomial (or Poisson) distribution accounts for. Thereby, these models tend to underestimate the percentage of zero purchases. A solution to this by Morrison and Schmittlein (1988) is to include a component to the model that allows for an additional spike at zero. This changes a Poisson or negative binomial model into a zero-inflated Poisson or negative binomial model. For this type of model, “the data are assumed to come from a mixture of two distributions where the structural zeros from a binary distribution are mixed with the non-negative integer outcomes (including zeros) from a count distribution. To model the structural zeros a logistic or probit regression is used and a Poisson or negative binomial regression is used for the count outcomes” (Hilbe, 2011, p. 36). Hence, we make use of zero-inflated negative binomial models for our purchase models.

Figure 2.K.1: Frequency plot of purchase study 1

Figure 2.K.2: Frequency plot of purchase study 2

Chapter 3

Should All Customers Be Multichannel?

Investigating the Moderating Role of Brand and Loyalty Tier²⁷²⁸

Abstract

The increasing number of sales channels provides firms with the opportunity to reach more consumers and provide them with more convenience. However, it also increases complexity for multichannel management. Existing studies support the (general) notion that a multichannel customer (compared to a single channel customer) is more profitable and thereby a multichannel strategy is more effective. However, current studies do not consider what happens to multichannel effectiveness when (1) a firm offers multiple brands (i.e., multi-brand firm), and (2) customer heterogeneity is considered. To provide insights into these prevailing issues, this chapter investigates whether multichannel customer behavior is always more valuable than single channel behavior by studying multichannel behavior effectiveness across brands and customer loyalty tiers. In contrast to conventional wisdom and prior literature, we show that multichannel customers do not always generate more revenue. Single channel customers (vs. multichannel customers) generate more revenue for the highest-level loyalty tier and for the combinations of highest-level loyalty tier and brand tiers. With these results, we strive to provide previously elusive insights into how to manage multichannel customer behavior at the multi-brand firm level. Thereby, we aim to provide firms with a precise understanding of the effectiveness of multichannel marketing in the context of multiple brands and taking into account consumer heterogeneity, and to help with the development of a promising multichannel strategy to grow revenue.

²⁷ This chapter is based on Lesscher, Lisan, Lara Lobschat, Katherine N. Lemon and Peter C. Verhoef (2020), “Should All Customers Be Multichannel? Investigating the Moderating Role of Brand and Loyalty Tier,” working paper.

²⁸ This chapter is also included in the MSI Working Paper Series: Lesscher, Lisan, Lara Lobschat, Katherine N. Lemon and Peter C. Verhoef (2020), “Should All Customers Be Multichannel? Investigating the Moderating Role of Brand and Loyalty Tier,” MSI Working Paper Series 2020, Boston, MA. Available at: <https://www.msi.org/working-papers/should-all-customers-be-multichannel-investigating-the-moderating-role-of-brand-and-loyalty-tier/>.

3.1. Introduction

The number of sales channels available to consumers is steadily growing (e.g., Marketing Science Institute 2018-2020). This offers firms opportunities for better reach and provides more convenience for consumers on the one hand, but also substantially increases complexity for multichannel management. Findings from existing studies predominately support the notion that a multichannel (vs. a single channel) strategy (i.e., offering multiple channels for purchase) is more effective, with multichannel customers being more profitable compared to single channel customers (e.g., Montaguti, Neslin, and Valentini, 2016; Kumar, Bezawada, and Trivedi, 2018). This is also supported by an industry study by IDC in 2015 which shows that the lifetime value of customers purchasing through multiple channels (compared to single channel) is 30% higher (Google, 2015). This might potentially also explain why firms are adding more and more sales channels to their channel portfolios. Case in point is the steady increase of firms using social media platforms (like Instagram) as sales channels (*AdWeek*, 2018). Nevertheless, only one third of marketers are confident in their ability to deliver a promising multichannel strategy (CMO, 2015). Hence, more insights into multichannel effectiveness for firms are required, which is also highlighted by the Marketing Science research priority on managing distribution across channels (Marketing Science Institute 2020-2022). Current multichannel studies have not unpacked what happens if (1) a firm offers multiple brands, and (2) when customer heterogeneity (e.g., regarding loyalty status) is considered. By taking these aspects into account, we contribute to both theory and practice by providing a more precise understanding of the effectiveness of multichannel marketing under different conditions.

First, current multichannel studies focus on a single brand, whereas many firms offer multiple brands within and across multiple product (and/or service) categories (i.e., multi-brand firms; see Ambler et al., 2002). For example, in the airline industry, the Lufthansa Group

comprises of brands like Lufthansa, Brussels airlines, and Eurowings (among others). The different brands (of the same firm) usually differ on service and/or price levels and serve as alternatives for consumers, although consumers can also buy multiple brands from the same firm (e.g., Kotler and Armstrong, 2018). These multi-brand firms can be found in industries like the travel & hospitality industry, the finance industry (e.g., banking and insurance industries), the FMCG industry (e.g., P&G), and the car industry. Hence, for marketing managers in these industries, the multichannel literature does not provide any guidance on how to operate multiple brands across an increasing portfolio of potential sales channels.

Additionally, the framework by Neslin et al. (2014) suggests that brand and channel choices are intertwined and jointly investigating them would provide a deeper understanding of consumer decision making in the modern marketing environment. Previous studies explore these choices separately (e.g., Thomas and Sullivan, 2005; Valentini, Montaguti, and Neslin, 2011; Russell, 2014). However, research exploring the interaction between consumers' brand and channel choice is scant. Thereby, we answer Neslin et al. (2014)'s call and integrate consumers' brand and channel choice in our study. More specifically, we investigate how multichannel (vs. single channel) behavior affects revenue outcomes and how this is moderated by consumers' brand choice in the presence of multiple brands of the same firm.

Apart from different brands, we also take customer heterogeneity (i.e., differences between customers) into account. In general, the effects of marketing and channel strategies are widely known (e.g., Hanssens, 2009), but we also know that these effects might differ for different customers (e.g., Herhausen et al., 2019). For example, there are studies suggesting that customers' commitment to maintain a relationship with a firm creates different responses to service failure (Hess, Ganesan, and Klein, 2003). Prior research also shows that customer responses differ between customer segments in a loyalty program (e.g., Kopalle et al., 2012) as well as loyalty formation differing between customers segments (e.g., Herhausen et al., 2019).

Therefore, we also consider customers' loyalty status as a moderator to account for customer heterogeneity. From the literature we know that loyalty affects the way consumers interact with a firm as well as consumers' purchase likelihood (e.g., Liu, 2007). Despite this, the moderating role of loyalty on the effect of customers' multichannel behavior on their revenue outcomes has not been considered by research yet. Hence, we propose that loyalty, in the interplay with the customers' brand choice among different brands and the sales channels s/he uses, needs to be taken into account.

This study also aims to contribute to the customer management and loyalty program literature. Most customer management studies investigate how their customer management practices affect loyalty and purchase outcomes, but do not take potential differences between brand(s) (tier(s)) into account. Although Ambler et al. (2002) and Leone et al. (2006) acknowledge the importance of considering the interface between customer management and brand management as both can be thought of as two sides of the same coin, it is largely neglected in existing studies (e.g., Valentini, Montaguti, and Neslin, 2011; Verhoef, 2003), probably because it is difficult to obtain appropriate data at this interface. Nevertheless, when considering both customer and brand management, this can help to improve the marketing success of a firm, whereas considering one without the other is unlikely to be as effective (Ambler et al., 2002; Leone et al., 2007). One exception is the study by Verhoef, Langerak, and Donkers (2007). They investigate the moderating role of brand tier on the contribution of the car dealer (in terms of quality, payment equity, trust, and switching costs) to customers' brand retention decisions. However, they do not take into account different sales channels and customer loyalty tiers. Most studies in the loyalty program literature focus on the effects of loyalty tiers on consumer purchase behavior (e.g., Kopalle et al., 2012; Drèze and Nunes, 2011). However, they do not consider multichannel behavior and/or brand tiers. Hence, differences in

the effects of multichannel behavior between customers with different loyalty status are not considered.

In sum, we investigate whether multichannel vs. single channel behavior generates less or more revenue by studying multichannel effectiveness across brand tiers and loyalty tiers. By investigating these research questions, we intend to provide more understanding on the effectiveness of the multichannel approach and thereby contribute to both theory and practice (see table 3.1 for our contribution relative to prior research).

In order to study our research idea, we make use of unique data from a large international hotel group, the Intercontinental Hotel Group (IHG). IHG is a multi-brand firm with multiple hotel brands which differ on their service and/or price levels. The data comprises longitudinal, transactional data for a sample of IHG customers from the firm's loyalty program. For each booked stay with the hotel group within our 1-year observation period, we have the required information on the loyalty tier of the customer at the time of purchase, what brand (tier) was purchased, and to what extent the customer is a multichannel or single channel customer. Furthermore, we have information on the revenue outcomes per purchase, particularly, revenue per stay. We analyze our data using a regression model for multichannel usage, across multiple brands, and loyalty tiers in order to answer and provide insights into our research questions. With our model, we also control for potential self-selection biases by employing propensity score matching. Our results enable firms to gain previously elusive insights into how to manage customers' multichannel behavior at the multi-brand firm level rather than just the brand level.

Overall, the results indicate that a multichannel strategy is more effective with multichannel customers generating more revenue compared to single channel customers. However, in contrast to conventional wisdom and prior literature, this is not always the case. Single channel customers generate more revenue for the highest-level loyalty tier and combinations of highest-level loyalty and brand tier customers. Our research provides insights into multichannel

effectiveness in terms of revenue across brand tiers and loyalty tiers and for different customer-brand combination(s). To identify these insights, we develop a Multi-Channel Share Index, which is a continuous measure on (the intensity of) multichannel behavior (see model development section) compared to the previously applied binary approach (e.g., Montaguti, Neslin and Valentini, 2016). Overall, we aim to help firms to get a deeper understanding of multichannel marketing effectiveness in order to gain the most value from and provide the most value to their customers. Our results suggest that firms should not “force” all customers into becoming multichannel; rather a more nuanced approach that accounts for brand and loyalty tiers may yield better revenue results.

In the next section, we present our conceptual framework followed by a review of relevant studies pertaining to the multichannel, customer management, brand management and loyalty program literature together with our expectations. Then, we describe the unique data and develop our model to answer our research question. Thereafter, we present the empirical results of our analyses and conclude with implications for research and practice.

Table 3.1: Contributions relative to prior research on multichannel effectiveness

Study	Aim	Study on multichannel effectiveness	Study impact of moderator(s)
Thomas and Sullivan (2005)	Provide multichannel retailers a communication strategy	✓	No
Kumar and Venkatesan (2005)	Analyze correlates of multichannel shopping behavior	✓	No
Venkatesan, Kumar and Ravishanker (2007)	Evaluate channel adoption duration	✓	No
Kushwaha and Shankar (2013)	Assess the moderating impact of product category characteristics on the channel preference–monetary value link	✓	✓ Product category characteristics
Cambra-Fierro et al. (2016)	Replicating Kushwaha and Shankar (2013) in a services context (banking)	✓	✓ Number and type of sales channels used
Montaguti, Neslin and Valentini (2016)	Evaluate whether marketing campaigns can induce multichannel buying (and profitability)	✓	No
Kumar, Bezawada and Trivedi (2018)	Assess the effects of multichannel shopping on customer spending, visit frequency, and customer profitability	✓	No
This paper (2020)	Study the moderating roles of brand tier and loyalty tier on the relationship between multichannel usage and revenue	✓	✓ Brand tiers and customer loyalty tiers

3.2. Conceptual framework

We develop a conceptual framework on how customers' multichannel behavior affects revenue outcomes and how this is moderated by their brand choice and current loyalty tier. Figure 3.1 depicts our conceptual framework. Following prior research (e.g., Kumar, Bezawada, and Trivedi, 2018), we start with investigating the main effect of multichannel behavior on purchase outcomes (1), in line with prior studies. To study the effect of multichannel behavior, we develop the *Multi-Channel Share Index (MCSI)*; see model development for more information on (the development of) this measure). *MCSI is a measure*

for the intensity of multichannel usage calculated per customer. It ranges from 0 to 1 with a high score on MCSI implying relatively more multichannel usage, while a low score on MCSI represents less multichannel usage with a score of 0 for single channel usage.

We continue with analyzing the potential moderating effects of brand tiers (2) and loyalty tiers (3) on the main effect of multichannel customer behavior on purchase behavior. In line with previous studies (e.g., Verhoef, Langerak, and Donkers, 2007; Verhoef, Pauwels, and Tuk, 2012), we propose that different (tiers of) brands can be understood in terms of (a set of) attributes, all at specific performance levels (Keller, 1998). In other words, a particular brand (tier) is purchased by consumers based on its attributes, such as price, quality or brand (image). Across the different brand tiers, consumers deem different attributes more important as found by Verhoef, Langerak and Donkers (2007). From a consumer perspective, we define a brand tier as *a (set of) brand(s) that consumers purchase based on the attribute(s) they deem important*. Following this definition together with the tiers introduced in the studies by Verhoef, Langerak, and Donkers (2007) as well as Geyskens, Gielens and Gijsbrechts (2010) on private label tiers, the choice for consumers consists of three types of brand tiers – low tier: economy tier, middle tier: volume tier, and high tier: luxury tier – following a “good, better, best” approach. The brand tiers vary along three dimensions: (1) price, (2) quality, in which we distinguish between the price-quality ratio of the tiers, and (3) brand (image). Figure 3.2 portrays how the brand tiers are positioned on the dimensions. The high brand tier (i.e., luxury tier) is classified as premium-priced and top-quality brand(s), ranking this brand tier at the top end of the market. The brand (image) of the brand tier is deemed very important as it is used to signal exclusivity, status, and wealth (e.g., Kirmani, Sood, and Bridges, 1999). The middle brand tier (i.e., volume tier) is the mid-price/mid-quality alternative. Quality is lower compared to the high tier brand, but so is the price. Also, the brand is of less importance with this brand tier as it is not purchased by consumers to communicate status, wealth or exclusivity. Lastly,

the low brand tier (i.e., economy tier) offers basic quality for the best price. Compared to the other tiers, the quality is lower but this also holds for the price. The brand is not important for these consumers as their main focus is on price. In sum, we can classify why consumers purchase the different brand tiers in the following way: For the lowest brand tier (i.e., economy tier) price is the main reason for consumers to purchase this brand (tier). The middle brand tier (i.e., volume tier) is purchased predominately for reasons such as value-for-money. Lastly, the high brand tier (i.e., luxury tier) is mainly purchased by consumers to signal exclusivity, status, and wealth. For each brand tier, the effect of multichannel shopping on revenue per stay might differ, which will be considered by studying the moderating effect of brand tier choice.

The customer loyalty tiers represent the (behavioral) loyalty of customers to a specific firm (e.g., Liu, 2007; Sharp and Sharp, 1997), as we will explain in the following. Similar to the study of Liu (2007), loyalty is defined as “a deeply held commitment to rebuy or repatronize a preferred product/service consistently in the future” (Oliver, 1999, p. 34), which is also in line with other definitions used in previous research (e.g., Herhausen et al., 2019; Blattberg, Kim and Neslin, 2008). Based on the definition of loyalty, consumers are more loyal when they consistently purchase from the firm implying increased purchases. This is conforming to the loyalty tiers we study. A customer loyalty program “assigns customers to segments or tiers and delivers different benefits to each tier” (Blattberg, Kim, and Neslin, 2008, p. 549-550). For each tier, the benefits differ with the most benefits being offered to the highest tier customers. In order to get to a higher loyalty tier, a customer has to increase purchase frequency and/or amount. Hence, consumers’ purchase behavior determines their assignment to a tier in the loyalty program with more purchases leading to the assignment to a higher loyalty tier. Thereby, a customer’s loyalty tier represents his/her behavioral loyalty to a firm. At the time of purchase, each customer in the loyalty program of IHG has a defined loyalty status as specified above. Dependent on the loyalty tier a customer resides in at the time of purchase, the effect of

multichannel shopping on revenue per stay might differ. Therefore, the moderating effect of loyalty tier will be taken into account.

Additional to our conceptual framework, we explore the three-way interaction between brand tiers and loyalty tiers by investigating the interactions between MCSI, brand tier and loyalty tier. Not all customers that purchase a specific brand (tier) have the same loyalty status. Similarly, not all customers with the same loyalty status purchase the same brand (tier) at each purchase incidence. Therefore, we explore whether the effect of multichannel behavior significantly differs for brand-loyalty tier combinations (e.g., a customer being in a lower loyalty tier buying a high-tier brand).

Figure 3.1: Conceptual framework

Figure 3.2: Positioning brand tiers along dimensions

Note: the color reflects the importance of the different dimensions for each brand tier with the darkness of the color increasing with importance, i.e., the darker the color, the more important consumers deem this dimension.

3.3. Hypotheses development

Prior literature investigates the effectiveness of multichannel customer behavior. Below, we review relevant studies pertaining to the multichannel, multichannel customer management, brand management as well as loyalty program literature, and motivate our hypotheses.

3.3.1. Main effect of multichannel behavior on purchase outcomes

The most important issues identified by past research include how multichannel behavior affects customer spending (e.g., Kumar, Bezawada and Trivedi, 2018), and profitability (e.g., Kumar, Shah, and Venkatesan, 2006) (also see Neslin and Shankar 2009 for a review). Thomas and Sullivan (2005) find evidence that multichannel customers purchase more frequently, more items, in more product categories, and generate more revenue for the firm compared to single channel customers. Moreover, results by Kumar and Venkatesan (2005, p. 44) indicate that multichannel customers provide higher returns, higher share of wallet, and have higher past customer value. Based on these findings, Venkatesan, Kumar and Ravishanker (2007) also find

a positive association between multichannel shopping and customer profitability through a longitudinal analysis. Likewise, Kumar, Shah and Venkatesan (2006) find multichannel behavior to be one of the antecedents of maximum positive impact to Customer Lifetime Value (CLV). Montaguti, Neslin and Valentini (2016) reveal that multichannel purchasing increases customer profit among multichannel customers compared to what they would have generated as non-multichannel customers. Kumar, Bezawada and Trivedi (2018) also find significant positive effects of multichannel behavior on customer spending, visit frequency and profitability.

Multiple studies also look into and explain what underlies the positive relationship between multichannel customer behavior and purchase outcomes (e.g., Kushwaha and Shankar, 2013; Neslin and Shankar, 2009; Liu, Lobschat, and Verhoef, 2018). Prior research by Kushwaha and Shankar (2013) outline several reasons why customer multichannel behavior increases customer spending: (1) additional sales channels provide greater convenience value for consumers, which lead to increased purchase frequency and accelerated purchases across multiple items and categories, (2) the wide assortment of products and/or services across different channels offers multiple opportunities for consumers to purchase (from the firm) and increase their spending, and (3) consumers can take advantage of the benefits that different sales channels provide to derive a higher value from them and, thereby, increase spending (e.g., Frazier, 1999). Overall, multichannel customers perceive value from using multiple sales channels. Following the argumentation by Kushwaha and Shankar (2013), we propose that being a multichannel or single channel customer serves as a proxy for customers' perceived value of and commitment to being a single or multichannel customer. Consequently, this perceived value and commitment positively affects consumer spending (e.g. Venkatesan, Kumar, and Ravishanker, 2007).

So, prior research (e.g., Ansari, Mela, and Neslin, 2008; Montaguti, Neslin, and Valentini, 2016) strongly suggests that multichannel shopping should increase customer spending. Therefore, our hypothesis (to replicate prior studies) is as following:

Hypothesis 1: Multichannel behavior has a positive effect on revenue per stay.

3.3.2. *Moderating effects on the relationship of multichannel behavior and purchase outcomes*

In addition to research showing the positive effect of multichannel behavior on purchase outcomes, there is some research considering the roles of moderators on the relation of multichannel behavior and purchase outcomes. Kushwaha and Shankar (2013) study the moderating effect of product category characteristics and find evidence that multichannel customers are the most valuable segment only for hedonic product categories. Cambra-Fierro et al. (2016) replicate the study by Kushwaha and Shankar by studying the influence of the type and number of channels used by customers in the banking industry. They find that fully multichannel customers – using all (four) available channels – are not the most profitable. However, concentrating all interactions through high-margin channels or specific channel combinations of two channels produces improvements in profitability. Building on these studies, we consider brand tier as well as customer loyalty tier as moderators and study whether multichannel effectiveness remains across different (combinations of) brand and loyalty tiers. We will explain our hypotheses on the effects of these moderators in the following.

3.3.2.1. *Multichannel behavior and brand (tier)*

Prior research shows that brand and channel perceptions together determine purchase (intentions) (Dodds et al., 1991). As outlined when explaining the brand tiers (also see figure 3.2), the different brand tiers interest different type of consumers as the tiers provide different value to consumers. Thereby, the positive effect of multichannel behavior on revenue might differ across the different brand tiers due to the value customers perceive from these brand tier choices. As stated, the high-tier brands are purchased by consumers to communicate

exclusivity, wealth and status. This is also suggested by economic theory indicating higher-tier brands are being bought by consumers to achieve greater social status (Veblen effect; Bagwell and Bernheim, 1996). Similarly, the branding literature also states that high-tier brands are purchased to communicate status (e.g., Kirmani, Sood, and Bridges, 1999). The status of a brand (tier) is, among other things, based on the customers' assumption that these brands are unique (e.g. Verhoef, Pauwels and Tuk, 2012). Thereby, high-tier brand customers deem the impact on their social network more important compared to consumers purchasing middle- or low-tier brands. The reasons multichannel behavior positively affects revenue outcomes, as outlined in section 3.3.1, pertain less to customers purchasing the high-tier brand(s) given their brand tier choice. The reasons boil down to multiple sales channels providing additional service to consumers, which consequently positively influence their satisfaction and purchase behavior (e.g., Blattberg, Kim and Neslin, 2008). However, customers purchasing the high brand tier gain most value from communicating their status, wealth and exclusivity, which leaves little room for the perception of additional value from multichannel behavior. This especially holds for reason (2) outlining increased availability of the firms' offerings by having multiple sales channels, which provides consumers with more opportunities to purchase from the firm. This additional value from multichannel behavior is not in line with the signal of exclusivity that high tier customers highly value. Consequently, this inconsistency may cause the customers to perceive less value in being a multichannel customer (i.e., using different sales channels) (e.g., Miyazaki, Grewal and Goodstein, 2005). Hence, the positive effect of multichannel behavior on revenue is expected to be lower for customers purchasing high-tier brands.

The lower-tier brands (i.e., economy tier) provide value to consumers in terms of price as this is the most important rationale to purchase the brand tier. For lower-tier brand customers, price is the most important attribute to assess the value of an offer and they do not focus on service attributes, which might explain why these customers do not perceive additional value

from multichannel behavior. Similar to the high-tier brands customers, being a multichannel customer is not perceived as adding value for low-tier brand customers. The additional service based on the additional sales channels is not perceived as such by these consumers given their focus to get the best price. Therefore, the positive effect of multichannel behavior on revenue is also expected to be lower for low-tier brand customers. Nevertheless, this is expected to be different for middle-tier brands (i.e., volume tier), which are not solely purchased for their price, but for their product and service attributes – value-for-money. Middle-tier brand customers value both price and service cues, which creates opportunities for multichannel behavior to add value for the consumers. Compared to high-tier and lower-tier brand customers, we expect middle-tier brand customers to perceive additional value by being a multichannel customer. Building on this, we hypothesize the following:

Hypothesis 2: The positive effect of multichannel behavior on revenue per stay is smaller for high-tier and low-tier brands compared to middle-tier brands.

3.3.2.2. Multichannel behavior and loyalty (tier)

Apart from the value of being a multichannel customer, the loyalty program also provides value to customers. Based on customers' purchase behavior, the loyalty program assigns customers to loyalty tiers and delivers different benefits based on the loyalty tier a customer resides in. Prior research in the loyalty program literature also studied the responses to loyalty tiers program and found differences (e.g., Kopalle et al., 2012; Drèze and Nunes, 2011). In the loyalty program, customers in the highest loyalty tier receive the highest level of service, whereas customers in the lowest loyalty tier receive relatively lesser service. Kopalle et al. (2012) support this by their finding that customer utility is increased by customer tier programs with more utility for higher tier benefits. In line with the reasoning of the moderating effect of brand tier, we expect that the additional value provided by multichannel behavior might add more value for less loyal customers (i.e., customers in a lower loyalty tier) compared to more

loyal customers (i.e., customers in higher loyalty tier). By that we imply that multichannel behavior will likely not be perceived to add much additional value for customers in high loyalty tiers as the loyalty program benefits to that loyalty tier already provide and contribute most of the value in terms of benefits and services. Customers residing in lower loyalty tiers receive less value from the loyalty program, which leaves room for multichannel behavior to provide value to these customers.

In addition to the highest loyalty tier benefits lowering the contribution of multichannel behavior, we acknowledge another characteristic of customers with this loyalty status that needs to be considered. In order to get to a higher loyalty tier, a customer has to increase purchase frequency and/or amount. Thereby, customers in the highest loyalty tier are customers that purchase most (frequently). From prior literature we know that the channel choice decision process of customers evolves over time (Valentini, Montaguti, and Neslin, 2011). The theoretical concept at work in this decision process – how a consumer will undertake determining which channel to use to make a purchase – is fundamentally one of learning. Following Gollwitzer and Bayer's (1999) theory, this suggests that consumers who have made few (many) purchases are less (more) certain of their goals and the channel matching their needs (i.e., channel preferences). Gensler, Verhoef and Böhm (2012, p. 987) support this learning process by providing evidence for the existence of channel experience effects²⁹ together with support that these effects explain a significant part of channel choices by consumers (i.e., the relative importance of experience effects is reported to sum up to 23%). These findings suggest that customers' channel choice decision process evolves over time with customers learning about a firm's channels to find their preferred channel for a given brand at a given point in time. Customers in the highest loyalty tier purchase most (frequently) and are therefore more loyal

²⁹ "Channel experience effects occur when using the channel increases the likelihood that the consumer will use the very same channel on the next occasion" (Gensler, Verhoef and Böhm, 2012, p. 987).

and experienced with the decision process. This type of customer is expected to have more clear goals and focus on their preferred channel matching these to gain the most value. Thereby, these customers do no longer perceive additional value of using multiple sales channels, as explained in section 3.3.1, when they increase their loyalty status. Having additional sales channels to choose from for (1) convenience, (2) having more opportunities to purchase from the firm or (3) to benefit from different sales channels to gain more value is not applicable to higher loyalty tier customers. These customers are loyal to the firm and are aware of specific sales channels that provide them with the most value. Hence, they do not perceive the additional value of multichannel behavior, which lowers the positive effect of multichannel behavior on revenue outcomes. Thus, we expect that the effect of multichannel behavior on purchase outcomes will be weakened when customers reside in higher loyalty tiers, making multichannel (vs. single channel) behavior less effective for higher loyalty tier customers. Formally, we hypothesize:

Hypothesis 3: The positive effect of multichannel behavior on revenue per stay will be weakened when customers reside in higher loyalty tiers.

3.4. Data

Our data come from a large international hotel group, the Intercontinental Hotel Group (IHG). IHG is a multi-brand firm with multiple hotels (i.e., brands) differing on their service and/or price levels. With the data, we will focus on the four main brands of the hotel group, for which specific hotel brands cannot be disclosed due to a non-disclosure agreement. The data comprises longitudinal, transactional data from a sample of customers from IHG's loyalty program³⁰. The final sample consists of 150,025 customers. In total, we have information on

³⁰ The original data set included transactional data for about 4 years with information on customers who were send (sales) promotions and whether or not they redeemed these promotions. However, given the focus of this research we excluded the customers who redeemed these promotions. Furthermore, we focus on a one-year time period, which has the least promotional activities (recognizing that the customers we study do not register for any promotions). Our data therefore does not include transactional data by customers who received promotions by IHG. As a robustness check, we estimated our focal model (as presented in section 3.5.4 multichannel model) on the original data set including the registered customers and control for registration (0 = no, 1 = yes) and find the results to be similar in sign, size and significance (see appendix 3.C).

around 1.1 million hotel stays divided over our sample of customers, who on average have 7.35 stays within our 1-year observation period. For each booked stay with the hotel group (i.e., purchase), we have data including the revenue outcomes, what brand (tier) was purchased, what sales channel was used and to what extent the customer is a multichannel or single sales channel customer, and the loyalty tier of the customer. Specifically, we examine revenue per stay as our dependent variable. All other information serves as control for our model, which will be specified in the model development chapter. Next, we will provide more detailed information on our data.

3.4.1. Channel information

For each customer, we have information on which channel was used to book a stay with IHG for the observation period of 1 year. The different channels can be found in table 3.2. Following prior research, we categorize the channels into firm-owned online (mobile app, web), firm-owned offline (central reservations, hotel direct), partner-owned online (online travel agency) and partner-owned offline (travel agency) (e.g., Lemon and Verhoef, 2016).

For all customers, we have information on which specific channel was used for each of the booked stays during the prior year(s) (i.e., starting the year before our observation period). This allows us to distinguish whether a customer uses the same channel (type) or different channels to book their stays over time. Moreover, we can calculate the frequency of channel usage of each channel for each customer at the time of each purchase. With this information, we can also estimate the Multi-Channel Share Index (MCSI), a measure for the intensity of multichannel usage. The development of this measure will be discussed in the model development chapter.

Table 3.2: Sales channels in the dataset

Channel	Description	Offline vs. online	Firm-owned vs. partner-owned
Web	Owned website of the firm	Online	Firm-owned
App	Owned mobile app of the firm	Online	Firm-owned
CRO	Central reservations office booking via voice interaction	Offline	Firm-owned
HTL	Hotel direct booking via voice or in-person interaction	Offline	Firm-owned
OTA	Online travel agency	Online	Partner-owned
GDS	Travel agent	Offline	Partner-owned
Other	Other channels, which could mean not being identified. Not considered in our study.		

Note: we acknowledge that customers are also faced with competing brands within partner-owned channels, which is not the case with firm-owned channels.

In the data, 42.4 % of the customers most frequently make use of online channels (mobile app, website and online travel agency), 57.6 % of offline channels (central reservations, hotel direct and travel agent). Of all customers, 98.7 % use firm-owned channels most frequently compared to 1.3 % using partner-owned channels most frequently. With regard to using multiple or single channels for their purchases over time, we see that 12.6 % of our customers have a MCSI score of 0 (= single channel user), while 31.9 % have a MCSI score above 0.5 indicating the customers are multichannel users.

3.4.2. Brand tier information

As stated, IHG is a multi-brand firm with multiple hotels (i.e., brands) differing on their service and/or price levels. For our data, we focus on the four biggest brands of the hotel group, which cannot be disclosed due to a non-disclosure agreement. Therefore, the brands are indicated with A, B, C, and D ranging from low to high on service and/or price levels (A lowest; D highest). Table 3.3 contrasts the brands (A, B, C and D) with regard to number of bookings, average spending, average number of nights, average MCSI score of customers, number of bookings for each current loyalty tier, and number of bookings for each sales channel category. This shows that the number of bookings is in line with the range of brands from low to high.

The higher the brand tier, the lower the number of bookings. Most bookings are for brand tier A (75%) followed by brand tier B (18%), brand tier C (5%) and lastly brand tier D (2%). Furthermore, the average spending increases with the level of brand tier with the lowest average spending for brand A and highest average spending for brand D. Similar effects can be identified for average number of nights, although the differences are less significant. In spite of this, we see that the average MCSI score of customers across all brand tiers are very similar.

With regard to the loyalty tier of customers, we see a similar pattern as with the number of bookings. The number of bookings is highest for brand A across all loyalty tiers. Within the different brands, the pattern is different as most bookings occur for loyalty tier 2 (and not loyalty tier 1 as the lowest loyalty tier). Lastly, we examine the sales channel share for each brand. We see that the number of bookings for online vs. offline sales channels have a very similar division for all brand tiers – offline sales channels have a share of 54%-59% for all brand tiers. The division between firm-owned and partner-owned sales channels is also highly similar across all brand tiers with the highest share for firm-owned sales channels (96%-99%).

Table 3.3: Profile of the brand tiers by IHG

	Brands			
	A	B	C	D
Number of bookings	783,193 (75%)	193,220 (18%)	56,817 (5%)	17,192 (2%)
Average revenue per stay	184.91	200.93	247.39	474.83
Average number of nights	1.60	1.66	1.88	2.21
Average MCSI score of customers	.347	.386	.358	.355
Loyalty tier of customers				
Loyalty tier 1	193,414 (75%)	46,406 (18%)	15,694 (6%)	3,454 (1%)
Loyalty tier 2	423,243 (75%)	103,541 (18%)	29,426 (5%)	9,498 (2%)
Loyalty tier 3	127,553 (74%)	32,546 (19%)	8,719 (5%)	3,360 (2%)
Loyalty tier 4	38,983 (73%)	10,727 (20%)	2,978 (5%)	880 (2%)
Sales channel share				
Offline	462,118 (76%)	104,365 (17%)	32,667 (5%)	9,739 (2%)
Online	319,127 (73%)	88,217 (20%)	23,723 (5%)	7,284 (2%)
Firm-owned	772,918 (75%)	189,382 (18%)	54,990 (5%)	16,379 (2%)
Partner-owned	8,327 (61%)	3,200 (24%)	1,400 (10%)	644 (5%)

3.4.3. Loyalty tier information

The loyalty program of IHG includes four loyalty tiers for the customers ranging from low to high (i.e., loyalty tier 1 is the lowest loyalty tier). Customers in the IHG loyalty program, the IHG Rewards Club, can be a Club Member (loyalty tier 1), Gold Elite Member (loyalty tier 2), Platinum Elite Member (loyalty tier 3), and Spire Elite Member (loyalty tier 4). In order to get to a higher tier, customers have to spend additional nights (thereby earn points) until they reach the threshold for the next tier level.

The data include information on customers' loyalty tier at the time of purchase. The customers are divided over the four loyalty tiers with the highest share of customers in loyalty tier 2 (Gold Elite Membership, 54%). Loyalty tier 1 (Club Membership) includes about 25% of

the customers, loyalty tier 3 (Platinum Elite Membership) about 16% and loyalty tier 4 (Spire Elite Membership) the lowest share with 5% of the total number of customers

3.4.4. *Revenue outcome*

For each booked stay, we have information on the revenue IHG earned with that stay, which is our dependent variable. When inspecting the distribution of this revenue variable, we observe two aspects that deserve attention: (1) the distribution is positively skewed (right-skewed), and (2) the variable takes very extreme values. The right-skewed distribution requires a log transformation for this variable (e.g., Wooldridge, 2012), which we will apply for our model. The extreme values of the variable were investigated. The data provider (IHG) informed us that the negative and very low values come from (1) customers using vouchers or points to book their stay, (2) conversion errors for stays outside of the United States or (3) (for very few observations) non-observable reasons. Therefore, we include controls for using vouchers and/or points and the region of the hotel for the stay. For the non-observable information, we consider deleting extreme values from the data. Therefore, we apply a method to delete $\pm$ three standard deviations of the mean for $\log(\text{revenue} + 1)$ (e.g., Howell, 1998; Iacobucci and Churchill, 2010)³¹. This leaves us with the data on 150,025 customers with in total around 1.1 million hotel stays. Revenue per stay will serve as the dependent variable in our analyses. On average, the room revenue per stay in the data is \$197.13 ranging from \$9 to \$2157.

3.5. Model development

We propose a model to investigate the multichannel effectiveness across brands and loyalty tiers. Therefore, we next discuss how we include the multichannel aspect, as well as the control variables, before going into the model specifications. We elaborate on our model development and the specific model we use in the following sections.

³¹ By applying the method of deleting $\pm$ three standard deviations of the mean, we delete 14% of the customers, which is equal to 18.5 % of the observations.

3.5.1. Multi-Channel Share Index (MCSI)

Our main interest is investigating the multichannel effectiveness across brand and loyalty tiers. However, this requires us to identify customers as multichannel or single channel customers. As indicated in the data section, we have information on which sales channels were used from the start of 2015 until the time of purchase by each customer and we can identify to what extent a customer used multiple or just a single sales channel to book his/her stay(s). Based on this information, we are able to use the frequency of usage of the different sales channels in order to get to the share of sales channel usage, i.e., how often a specific sales channel was used out of the total number of times the customers used the sales channels. With this share of sales channel usage, we can model the share of multichannel usage in line with the Herfindahl-Hirschman Index (HHI) (Hirschman, 1945; Herfindahl, 1950). The Herfindahl-Hirschman Index (HHI) is a common measure of market concentration and its reverse is used to determine market competitiveness. If we apply this measure to our sales channel usage setting, we can create a measure for the intensity of multichannel usage calculated per customer. We term this measure as the Multi-Channel Share Index (MCSI). The equation of this measure can be found in equation 1.

$$MCSI_{it} = 1 - \left(\frac{\text{share}_{web_{it}}^2 + \text{share}_{app_{it}}^2 + \text{share}_{htl_{it}}^2 + \text{share}_{cro_{it}}^2}{\text{share}_{ota_{it}}^2 + \text{share}_{gds_{it}}^2 + \text{share}_{other_{it}}^2} \right) \quad (1)$$

Where $\text{share}_{channel_{it}}$ refers to the share of sales channel usage by a customer, which translates into how often that specific sales channel was used by this customer out of the total number of times the customer used the sales channels. MCSI ranges from 0 to 1 with a high score on MCSI implying more multichannel usage by the customer, while a low score on MCSI implies less

multichannel usage by the customer, i.e., single channel usage for a score of 0³². In our data, the mean MCSI is 0.36 ranging from 0 to 0.84.

We provide an illustrative example of the calculation of our measure for 5 fictitious customers in table 3.4. Even though the customers are fictitious, the patterns of sales channel usage are realistic. Based on the usage of each sales channel together with the total number of bookings, the share of sales channel usage by customer i at time t (purchase incidence) can be calculated and squared. These (squared values of) shares are used to calculate MCSI by subtracting the sum of squared shares from 1. Customer A shows a customer using only one sales channel leading to a score on MCSI of 0 (i.e., single channel customer), the minimum score on MCSI. Customers B, C, D and E use multiple sales channels with customer B using all channels equally, leading to the maximum score of MCSI in our empirical setting and data. Customer C uses two channels equally leading to a score of .5 and customer D uses four channels equally leading to a score of .75. Lastly, customer E uses multiple sales channels of which half of its bookings were purchased through the same channel. All in all, the illustration shows that the more sales channels are used by the customer, the higher the value on MCSI becomes. Furthermore, customer E shows the difference in the extent of multichannel behavior given that this customer uses multiple sales channels while focusing on one of the channels. The MCSI score reflects this by showing a lower score compared to customer D although the same number of sales channels are utilized. In sum, the MCSI reflects the intensity of multichannel behavior.

³² Besides the MCSI, we also conduct robustness check with our model including the binary variable multichannel users (0 = MCSI score of 0 indicating single channel users, 1 = MCSI score above 0.5 indicating multichannel users) and results are robust (also see section 3.6.3 robustness checks and appendix 3.C).

Table 3.4: Illustration of Multi-Channel Share Index (MCSI)

	Customer A		Customer B		Customer C		Customer D		Customer E	
<i>Channel</i>	<i>Number of bookings</i>	<i>share²</i>	<i>Number of bookings</i>	<i>share²</i>	<i>Number of bookings</i>	<i>share²</i>	<i>Number of bookings</i>	<i>share²</i>	<i>Number of bookings</i>	<i>share²</i>
Web	0	0	1	.0204	1	.25	1	.0625	3	.25
App	1	1	1	.0204	0	0	1	.0625	1	.0278
HTL	0	0	1	.0204	1	.25	1	.0625	0	
CRO	0	0	1	.0204	0	0	1	.0625	0	
OTA	0	0	1	.0204	0	0	0	0	1	.0278
GDS	0	0	1	.0204	0	0	0	0	1	.0278
Other	0	0	1	.0204	0	0	0	0	0	
<i>Total number of bookings</i>	1		7		2		4		6	
MCSI (1 - $\Sigma(\text{share}^2)$)		0		.8571		.5		.75		.67

3.5.2. *Control variables*

In order to control for multiple aspects, which might serve as confounds, we also include control variables in our models. For each of the customers, we know the time elapsed (in days) between this current booking and last booking (= recency), how often the customers booked before (= frequency) and the average spending across the previous made purchases. All of these aspects are taken into account to account for the potential developments of effects over time. Furthermore, the customers may use specific brands and channels most frequently, which might cause bias in our results (e.g., self-selection bias). To control for this aspect, we use information on the dominant brand and channel of each customer at the time of each purchase. The dominant brand (channel) is the brand (channel) that is used most frequently by the customer for their past purchases³³. Also, we have information on whether the customer redeemed points to purchase or used a free night voucher or bonus point package rate for their purchase, which we include in our model as a binary control variable. Furthermore, location might affect consumer behavior for example given its influence on room rates in the hotel setting (e.g., Zhang, Ye, and Law, 2011), which is why we include a control indicating whether the customer booked a stay in their home region or not. We also include the key for each region in the model to control for this potential geographical effect. Lastly, the data include both business and leisure bookings. We are able to account for whether customers are traveling for business or leisure by including a proxy indicating whether the booking was made using a corporate rate. To check this operationalization, we conduct a robustness check including a control indicating whether the booked stay includes nights on the weekend (as business trips are not common to take place in

³³ The dominant channel and brand variables are calculated based on the frequency of channel (brand) usage of each channel (brand) for each customer at the time of each purchase. By knowing the frequency of usage of a specific channel or brand, we can determine the most frequent used channel (purchased brand) of each customer at each time, which we term as the dominant channel (brand) by that customer at that time of purchase. In case of an even distribution, one of the most frequently used channels (purchased brands) is selected as the dominant option.

the weekend). Results are similar in sign and significance when replacing the proxy with this control (see section 3.6.3 for the robustness check).

3.5.3. *Self-selection issue*

Despite the finding of prior multichannel research showing multichannel purchasing to be associated with higher purchase outcomes, the main question is why this is the case and what underlies this relationship. Therefore, past research lists reasons for multichannel shopping being more profitable (e.g., Neslin et al., 2006; Neslin and Shankar, 2009; Montaguti, Neslin, and Valentini, 2016) with self-selection being one of the (main) reasons. The self-selection explanation is that customers, who have higher purchase volumes, have more purchase occasions making them naturally use more channels (e.g., Blattberg, Kim, and Neslin, 2008). Hence, customers become multichannel (i.e., use multiple sales channels) because of their higher purchase volumes. We control for this self-selection as various studies indicate that ignoring self-selection biases lead to inaccurate estimation of the multichannel effects (e.g., Gensler, Leeflang, and Skiera, 2012). For this purpose, we employ propensity score matching to control for self-selection when studying multichannel behavior (e.g., Montaguti, Neslin, and Valentini, 2016).

The basic idea of propensity score matching (PSM) in our context is to find a matched sample of non-multichannel customers, who have the closest propensity scores to those of the sample with multichannel customers. The propensity score is the probability that a unit in the full sample received the treatment (here: being a multichannel customer ($MCSI > 0.5$)), given a set of observed characteristics (Dehejia, 2005). By applying this method, we can ensure the distribution of characteristics is similar for both groups (Rosenbaum and Rubin, 1985).

We dichotomize our continuous MCSI measure to a binary treatment variable indicating customers to be more multichannel ($MCSI \geq .5$) or to be more single channel (e.g., using a single sales channel or focus highly on a single sales channel; $MCSI < .5$). With this binary

variable, we conducted a binary logistic regression model to estimate the probability that a customer is a multichannel customer, as a function of the dominant brand of customers and his/her prior purchase behavior (including recency, frequency and average spending of prior purchases). Given that the self-selection explanation indicates that multichannel customers purchase more often, prior purchase behavior variables are included to match customers. Following the rules of one-to-one matching, a multichannel customer in the data is matched to a non-multichannel customer with the closest propensity score. The resulting data with matched customers is used to estimate our model³⁴ (for more information see equation 2 in section 3.5.4.), in addition to estimating the model with the non-matched data.

3.5.4. Multichannel model

In order to analyze the effectiveness of multichannel strategy, we propose a model with the revenue per stay for customer i at time of purchase t as our dependent variable of interest. MCSI score up until the current time of purchase ($t-1$) as well as brand tier and customer loyalty tier – both for customer i at purchase occasion t – together with our control variables serve as independent variables, as shown in equation 2³⁵. Hence, taking into account all discussed aspects of the model development, the (full) model is specified as follows:

$$\begin{aligned} \log(\text{Revenue}_{it}) = & \alpha + \beta_1 \text{MCSI}_{it-1} + \beta_2 \text{Brand}_{it} + \beta_3 \text{LT}_{it} + \beta_4 \text{Brand}_{it} * \text{MCSI}_{it-1} \\ & + \beta_5 \text{LT}_{it} * \text{MCSI}_{it-1} + \beta_6 \text{Brand}_{it} * \text{LT}_{it} + \beta_7 \text{Brand}_{it} * \text{MCSI}_{it-1} * \text{LT}_{it} \\ & + \beta_8 \text{recency}_{it} + \beta_9 \text{frequency}_{it} + \beta_{10} \text{avgspending}_{it} + \beta_{11} \text{homeregion}_{it} \\ & + \beta_{12} \text{corporaterate}_{it} + \beta_{13} \text{brandpref}_{it} + \beta_{14} \text{voucher_use}_{it} \\ & + \beta_{15} \text{redeemingpoints}_{it} + \beta_{16} \text{bpp_use}_{it} + \beta_{17} \text{region}_{\text{key}_{it}} \\ & + \beta_{17} \text{channelpref}_{it} + e_{it} \end{aligned} \quad (2)$$

In this model, we define the variables as follows:

³⁴ Additional to estimating our model with the continuous MCSI measure using this data with matched customers, we also estimated our model with the binary variable for multichannel behavior we apply for propensity score matching and results remain robust.

³⁵ For the estimation of our specified model, we build up the model in the following way: (1) we start with our model only including the main effects of MCSI, brand and loyalty tier, (2) we include our controls to model 1, (3) we include the interactions between MCSI and brand, MCSI and loyalty tier and brand and loyalty tier in model 2, and (4) we include the three-way interactions between brand, loyalty tier and MCSI in model 3. Lastly, we estimate our specified model with the matched data from PSM in model 5.

$\log(\text{Revenue}_{it})$	the natural logarithm of the room revenue for one stay by customer i at time t
Brand_{it}	the purchased brand tier (A, B, C, D) for customer i at time t with brand A (i.e., brand with lowest service/price level) being the reference level
LT_{it}	the loyalty tier (1 – 4) for customer i at time of purchase t with loyalty tier 1 (i.e., lowest loyalty tier) being the reference level
MCSI_{it}	the Multi-Channel Share Index for customer i at time t
recency_{it}	the time elapsed (in days) since the last booking for customer i at time t
frequency_{it}	the number of times the customer i booked before at time t
avgspending_{it}	the average spending across the previous purchases (from 2015 until time t) for customer i at time t
homeregion_{it}	whether customer i booked a stay in his/her home region (=1) or not (=0) at time t
$\text{corporaterate}_{it}$	whether the booking was made using a corporate rate (=1) or not (=0)
dombrand_{it}	the dominant (= most frequently purchased) brand tier (A, B, C, D) for customer i at time t
voucher_use_{it}	whether the booking was made using a free night voucher (=1) or not (=0) for customer i at time t
$\text{redeemingpoints}_{it}$	whether the booking was made by redeeming points (=1) or not (=0) for customer i at time t
bpp_use_{it}	whether the booking was made using a bonus point package rate (=1) or not (=0) for customer i at time t
regionkey_{it}	the key that identifies a geographic region where the associated hotel is located for customer i at time t
domchannel_{it}	the dominant (= most frequently used) channel for customer i at time t

Before estimating our model, we checked whether multicollinearity is an issue with our model specification by checking the correlations between the independent variables (see correlation table in appendix 3.A). Given that frequency is (highly) correlated with loyalty tier ($r = .65$) and dominant brand with purchased brand ($r = .54$), we opted to not include frequency and dominant brand as controls in order to circumvent potential multicollinearity issues. Nonetheless, the results of the models with and without the correlated controls are (highly) robust, which serves as an indication that multicollinearity does not pose a serious concern (Leeflang et al., 2015). Furthermore, the VIF values of the model including all control variables do not exceed a value of 4, which is well below the threshold (e.g., Leeflang et al., 2015). Therefore, we present the models with all controls.

3.6. Results

An overview of our results is provided in table 3.5. According to the multichannel model, multichannel behavior generates higher revenues (compared to single channel behavior), but this is not always the case. Before discussing the results of our models, we first present our initial model-free analyses.

3.6.1. Model-free results

First, we explore the revenue per stay outcome for the different brand tiers, loyalty tiers and multichannel share index (MCSI) scores by conducting simple t-tests. In general, we find that higher brand tiers are associated with higher revenue per stay. This also holds for higher loyalty tiers. When comparing MCSI scores of 0 with MCSI scores of .50 or higher, which is equal to comparing single channel users and (more) multichannel users, we find the following: overall, there is no significant difference between single channel users and multichannel users ($M_{\text{single}} = 205.52$, $M_{\text{multi}} = 204.77$, $p > .05$). However, we do find significant differences when comparing single and multichannel users for the different brands. For brand tiers A and C, multichannel users have a higher revenue per stay compared to single channel users (A: $M_{\text{single}} = 188.65$, $M_{\text{multi}} = 191.32$, $p < .001$; C: $M_{\text{single}} = 246.44$, $M_{\text{multi}} = 262.23$, $p < .001$). For brand tiers B and D, multichannel users have a lower revenue per stay compared to single channel users (B: $M_{\text{single}} = 214.92$, $M_{\text{multi}} = 206.25$, $p < .001$; D: $M_{\text{single}} = 509.87$, $M_{\text{multi}} = 486.43$, $p < .01$).

Furthermore, we do find significant differences when comparing single and multichannel users for the different loyalty tiers. For loyalty tier 1, multichannel users have a higher revenue per stay compared to single channel users ($M_{\text{single}} = 191.45$, $M_{\text{multi}} = 193.69$, $p < .001$). For loyalty tier 2, 3 and 4, multichannel users have a lower revenue per stay compared to single channel users (2: $M_{\text{single}} = 214.51$, $M_{\text{multi}} = 203.80$, $p < .001$; 3: $M_{\text{single}} = 229.67$, $M_{\text{multi}} = 218.27$, $p < .001$; 4: $M_{\text{single}} = 248.58$, $M_{\text{multi}} = 225.84$, $p < .01$).

When looking at the difference between single and multichannel users for all combinations of brand-loyalty tier customers, model-free results indicate that in general, across all brands, multichannel users have higher revenue per stay for the lowest loyalty tier, whereas single channel users have higher revenue for the highest loyalty tier³⁶. This implies that more loyal customers are more valuable when using a single sales channel to book their stays, whereas less loyal customers (potentially new customers) are more valuable when using multiple channels to book their stays.

3.6.2. *Model results*

Table 3.5 shows the parameter estimates of our multichannel model (equation 2) that are used to answer our research questions (the results of the control variables can be found in appendix 3.B). The table includes the results of multiple models, which include all variables of our equation 2 step by step (see section 3.5.4. and footnote 35 for more explanation on build up). Models 1 – 4 are estimated using the non-matched data (i.e., before PSM), while model 5 estimates our specified model from equation 2 on the matched data³⁷³⁸.

In line with prior research, the main effect of MCSI – multichannel behavior – on revenue per stay is positive and significant (for all models). That is, a higher MCSI score – intensive multichannel usage – increases the average revenue per stay. With this finding, we replicate prior findings (e.g., Ansari, Mela, and Neslin, 2008; Montaguti, Neslin, and Valentini, 2016) and, thereby, find support for our first hypothesis.

³⁶ Given the high number of tests for these model-free results, these are not reported here. The results are available on request.

³⁷ Model 5 in table 3.5 does not include the three-way interactions as the F-test to compare the models including and excluding the three-way interactions show that the model fit does not improve by including the three-way interactions ($F = 1.51, p = .14$). Furthermore, the (adjusted) R-square does not improve and the AIC (1,166,481 vs 1,166,477) and BIC (1,167,072 vs 1,166,955) of the model including the three-way interactions (vs. the model excluding the three-way interactions, respectively) are higher.

³⁸ In the following, we report the estimates of model 3 unless indicated otherwise. However, the results of the other models are in line with these results (see table 3.5).

When we examine the estimates of the interactions between MCSI and brand tier as well as MCSI and loyalty tier, we observe that multichannel customers do not always generate more revenue per stay. Across the brand tiers, we find higher revenues per stay for higher MCSI scores (i.e., intensive multichannel usage). For all models, the interaction between MCSI and brand tier C (i.e., upscale brand) is positive and significant ($\beta_{4,C} = .17, p < .001$). For model 3 and 5 (see table 3.5), the interaction between MCSI and brand tier D (i.e., luxury brand) is also significant and positive ($\beta_{4,D} = .07, p < .001$ and $\beta_{4,D} = .08, p < .01$, respectively), whereas the interaction between MCSI and brand tier B is only marginally significant for model 5 showing a positive effect (model correcting for self-selection with PSM) ($\beta_{4,B} = .02, p < .10$). These findings provide support for H2 as the effects are smaller for the lower-tier (e.g., brand tiers A and B) and higher-tier brands (e.g., brand tier D) compared to middle-tier brands (e.g., brand tier C). In addition to the model results, we estimate and test the simple effect of the MCSI at different levels of the moderator brand tier with a spotlight analysis (Spiller et al., 2013). The spotlight analysis supports that all linear combinations of MCSI and brand tier are significant ($p < .001$).

For all loyalty tiers, the interaction with MCSI on revenue per stay is negative and significant ($\beta_{5,LT2} = -.03, p < .001$; $\beta_{5,LT3} = -.06, p < .001$; $\beta_{5,LT4} = -.14, p < .001$). Thereby, findings show that the revenue per stay for customers with a higher loyalty tier at the time of purchase decreases when their MCSI score is higher (i.e., intensive multichannel usage). That is, a higher MCSI score for customers with loyalty tier 2, loyalty tier 3 and loyalty tier 4 decreases average revenue per stay. This finding is in line with H3. More loyal customers seem to spend less when using a higher number of sales channels. Despite the negative interaction effects for all loyalty tiers, we only see that single channel customers (vs. multichannel customers) generate more revenue per stay for loyalty tier 4 (i.e., highest loyalty tier), which will be elaborated in the scenario analysis. Again, we additionally estimate and test the simple

effect of the MCSI at different levels of the moderator loyalty tier with a spotlight analysis (Spiller et al., 2013). The spotlight analysis supports that all linear combinations of MCSI and loyalty tier are significant ($p < .01$).

Lastly, we turn to the model with three-way interactions – model 4 – to explore the differential effect of customers with specific combinations of purchased brand tier and customer loyalty tier. When exploring the effects of the three-way interactions, results show that some customer combinations of higher brand tiers and customer loyalty tiers decrease customer spending when MCSI scores increase. This result is in line with our model-free evidence indicating that the customer combinations of higher loyalty tiers and brand tiers have higher average revenue per stay for single channel users. How this translates into revenue per stay for the different brand-loyalty combinations will be provided in the scenario analysis in section 3.7.

In addition to the expectations and effects from the conceptual framework, we can investigate some of the other estimates. In line with our expectations, and given that higher brand tiers have a higher price level, we find that the average revenue per stay increases with higher brand tiers ($\beta_{2,B} = .06, p < .001$; $\beta_{2,C} = .12, p < .001$; $\beta_{2,D} = .70, p < .001$). This result is significant and positive for all models. Similarly, we find, for all models, that the effects of loyalty tier are significant and positive ($\beta_{3,LT2} = .07, p < .001$; $\beta_{3,LT3} = .20, p < .001$; $\beta_{3,LT4} = .35, p < .001$). That is, the average revenue per stay increases when customers have a higher loyalty tier, which is in line with prior research (e.g., Kumar and Shah, 2004).

Regarding the parameter estimates of the control variables, these can be found in appendix 3.B. For all models, the effect of recency and average spending is significant and (slightly) positive ($\beta_8 = .00, p < .001$; $\beta_{10} = .00, p < .001$), whereas the effect of frequency is significant and (slightly) negative ($\beta_9 = -.00, p < .001$). This implies that recency and average spending (slightly) increases customer spending, but frequency decreases customer spending. This is in

line with previous studies (e.g., Ansari, Mela, and Neslin, 2008). Furthermore, the effect of corporate rate is negative ($\beta_{12} = -.02, p < .001$), which can be expected given that corporate rates are mostly lower. For dominant brand, we find that the average revenue per stay is lower for customers that book another brand than their dominant brand. Customers using a free night voucher or redeeming points to book their stays have a lower revenue per stay, as their voucher or points allow them to pay a lower amount ($\beta_{14} = -1.22, p < .001$; $\beta_{15} = -1.35, p < .001$). The effect of customers using a bonus point package rate is positive ($\beta_{16} = .05, p < .001$). When booking using this rate, customer have to pay the full amount of a room, but can earn more bonus points. Therefore, this differs from a free night voucher or redeeming points and the effect is different and in line with expectations. The more customers spend when using this rate, the more points they earn.

Table 3.5: Model results

	Model 1		Model 2		Model 3		Model 4		After PSM Model 5	
Intercept	4.88	***	4.73	***	4.72	***	4.72	***	4.75	***
<i>Main effects</i>										
MCSI	0.11	***	0.08	***	0.10	***	0.10	***	0.09	***
Brand B	0.02	***	0.04	***	0.06	***	0.05	***	0.05	***
Brand C	0.22	***	0.18	***	0.12	***	0.13	***	0.15	***
Brand D	0.89	***	0.64	***	0.70	***	0.72	***	0.70	***
Loyalty tier 2 (LT 2)	0.05	***	0.06	***	0.07	***	0.07	***	0.07	***
Loyalty tier 3 (LT 3)	0.09	***	0.18	***	0.20	***	0.20	***	0.21	***
Loyalty tier 4 (LT 4)	0.13	***	0.30	***	0.35	***	0.34	***	0.34	***
<i>Interaction effects</i>										
Brand B*MCSI					-0.00		0.01		0.02	.
Brand C*MCSI					0.17	***	0.15	***	0.11	***
Brand D*MCSI					0.07	***	0.01		0.08	**
LT2*MCSI					-0.03	***	-0.03	***	-0.04	***
LT3*MCSI					-0.06	***	-0.04	***	-0.08	***
LT4*MCSI					-0.14	***	-0.11	***	-0.15	***
Brand B*LT2					-0.01	***	-0.01	*	-0.02	***
Brand C*LT2					-0.01	*	-0.04	***	-0.01	
Brand D*LT2					-0.09	***	-0.12	***	-0.10	***
Brand B*LT3					-0.01	**	0.01		-0.02	***
Brand C*LT3					-0.03	***	-0.02		-0.03	**
Brand D*LT3					-0.17	***	-0.20	***	-0.14	***
Brand B*LT4					-0.02	**	0.01		-0.02	*
Brand C*LT4					0.01		0.07	**	-0.00	
Brand D*LT4					-0.13	***	-0.13	**	-0.12	***
Brand B*LT2*MCSI							0.00			
Brand C*LT2*MCSI							0.07	**		
Brand D*LT2*MCSI							0.07			
Brand B*LT3*MCSI							-0.08	***		
Brand C*LT3*MCSI							-0.01			
Brand D*LT3*MCSI							0.08			
Brand B*LT4*MCSI							-0.07	*		
Brand C*LT4*MCSI							-0.19	**		
Brand D*LT4*MCSI							-0.00			
Adjusted R-square	.0324		.3553		.3556		.3556		.3494	
AIC	2,241,724		1,815,260		1,814,727		1,814,698		1,166,477	
BIC	2,241,831		1,815,580		1,815,225		1,815,303		1,166,955	

. $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

3.6.3. *Robustness checks*

In addition to our analyses, we also examined whether our results are robust to different model specifications. With the current transactional data, we do not consider the incidences where customers do not purchase. Therefore, we also checked whether our results are robust when estimating our model on data across customers, only. We aggregated our data to a customer level, where we have the average revenue per stay for each customer, the MCSI for the entire year, the dominant brand in that year, the customer loyalty tier at the start of the year and averages of our controls. When estimating our specified model using this customer level data, we find our results to remain highly similar (see appendix 3.C). One exception to this is for the interactions between brand tier and MCSI, which turn significant for brand tiers B and D with a negative effect. We believe this can be explained by the fact that brand tier in this model is not the purchased brand, but the most frequently purchased brand in that year (i.e., dominant brand). For customers with the dominant brand being B or D, a higher MCSI score – intensive multichannel usage – decreases the average revenue per stay.

To further determine the robustness of our findings, we performed additional checks. Another way to examine the impact of multichannel usage is to compare multichannel customers to single channel customers (as with the model-free results comparing MCSI scores of 0 with MCSI scores of .50 or higher). Therefore, we estimate our models with this binary variable (instead of the continuous MCSI score). Second, instead of using corporate rate to distinguish between business and leisure, we also estimated our model using a control indicating whether the booked stay includes weekend nights or not. Third, we performed a robustness check in which we use data on the entire year for the variables MCSI, dominant brand and dominant channel. This implies that MCSI, dominant brand and dominant channel has no time subscript (i.e., only differs across customer) and is calculated afterwards for an entire year. Fourth, we estimate our model with number of nights as the dependent variable

(instead of revenue per stay). Lastly, we also performed a robustness check in which we use the data including the customers, who registered for any promotional activities by the firm, and control for this registration by including it as a control. The results of these robustness checks can be found in appendix 3.C. Across all robustness checks, we find support for our main results establishing confidence in our findings.

3.7. Scenario analysis

Additional to our results and robustness checks, we demonstrate how strong the effect of multichannel compared to single channel customers is for all brand tiers, customer loyalty tiers and brand-loyalty tier combinations. When analyzing large volumes of data, it is important to also focus on effect sizes, whether the effects are substantive and if they have managerial meaning other than merely being statistically significant (Verhoef, Kooge, and Walk, 2016). For this purpose, we use the parameter estimates from model 3 and 4 in table 3.5³⁹ and translate these estimates (i.e., the effect sizes) into revenue outcomes for specific brand tier and/or loyalty tier customers. The main findings are very similar when we use the estimates of the other specified models.

In the simulation, we investigate the effect of multichannel behavior (intensity of multichannel usage based on the MCSI score) by incorporating the different brand tiers, customer loyalty tiers and brand-loyalty tier combinations of customers (e.g., a customer residing in loyalty tier 4 purchasing brand tier B). Out of all different brand-loyalty tier combinations, we consider six scenarios: (1) a customer with loyalty tier 1 purchasing brand tier A, (2) a customer with loyalty tier 2 purchasing brand tier B, (3) a customer with loyalty tier 3 purchasing brand tier C, (4) a customer with loyalty tier 3 purchasing brand tier D, (5) a

³⁹ We use the estimates of these models as their model fit is highly similar and one of the models includes the three-way interactions, which is needed to estimate the revenues for brand-loyalty tier combinations. Model 3 is used for table 3.6 and model 4 for table 3.7.

customer with loyalty tier 4 purchasing brand tier C, and (6) a customer with loyalty tier 4 purchasing brand tier D⁴⁰.

For the effect of multichannel behavior, we consider multiple MCSI scores indicating the intensity of multichannel behavior. For example, a customer using a single channel has a MCSI score of 0, whereas a customer using two sales channels equally has a MCSI score of 0.5. For our scenario analyses, we look at four type of customers based on their MCSI: (1) a MCSI of 0 (i.e., single channel customer), (2) a MCSI of 0.33, (3) a MCSI of 0.5, and (4) a MCSI of 0.84 (i.e., maximum value of MCSI in our data). For each value of MCSI, we calculate the (average) revenue per stay across the different brand tiers, customer loyalty tiers and brand-loyalty tier combinations of customers^{41,42}.

Tables 3.6 and 3.7 contain the output of the scenario analyses. In table 3.6, we find higher average revenue per stay for higher MCSI scores across all brand tiers. Similarly, higher average revenue per stay is found for higher MCSI scores across all customer loyalty tiers, except for the highest loyalty tier – customer loyalty tier 4. For this loyalty tier, we see that revenue per stay decreases when customers have higher MCSI, which implies higher multichannel usage. The highest revenue per stay is for a MCSI of 0, meaning single channel customers.

In table 3.7, we study multiple brand-loyalty tier combinations of customers. Again, we find that higher MCSI lead to higher revenue per stay for most combinations. However, this is not the case for customers in loyalty tier 4 purchasing brand tiers C or D. For these combinations,

⁴⁰ If interested in results for other brand-loyalty tier combinations, the authors can be contacted.

⁴¹ For the different loyalty tiers, we use the parameter estimates assuming the customer purchased brand tier A (reference level). The same holds for the parameter estimates of the brand tiers, which represent their effect for loyalty tier 1 customers. Nevertheless, the differences in revenue for all brand and loyalty tiers remain the same when adding the additional revenue based on another reference brand/loyalty tier.

⁴² To calculate the revenue outcomes, we make use of the estimates of interest, which take into account the variance explained by all control variables. We calculate the revenue outcome by summing the estimates of the variables of interest (i.e., brand/loyalty tier and their interaction) together with the MCSI estimate for the specified value of MCSI and lastly, back-transform the log dependent variable.

we see that higher MCSI decreases the revenue per stay. Consequently, we also checked whether this is the case for customers in loyalty tier 4 purchasing brand A and B. For these brand-loyalty tier combinations, the revenue per stay decreases when MCSI increases. Together, the scenario analyses confirm our model results and make the model results more concrete in terms of revenue.

Table 3.6: scenario results across brand tiers and loyalty tiers

Scenario	Brand A	Brand B	Brand C	Brand D	Loyalty tier 1	Loyalty tier 2	Loyalty tier 3	Loyalty tier 4
MCSI = 0	112.17	119.10	126.47	225.88	112.17	120.30	137.00	159.17
MCSI = .33	115.93	123.10	138.26	238.91	115.93	123.11	138.82	157.09
MCSI = .5	117.92	125.21	144.75	245.92	117.92	124.59	139.77	156.02
MCSI = .84	122.04	129.59	158.83	260.72	122.04	127.62	141.71	153.89

Table 3.7: scenario results across brand-loyalty tier combinations

Scenario	Brand A LT 1	Brand B LT 2	Brand C LT 3	Brand C LT 4	Brand D LT 3	Brand D LT 4
MCSI = 0	112.17	126.47	156.02	192.48	230.44	284.29
MCSI = .33	115.93	129.85	167.22	189.33	235.05	283.35
MCSI = .5	117.92	130.32	173.30	187.73	237.46	282.87
MCSI = .84	122.04	135.30	186.27	184.53	242.41	281.90

3.8. General discussion

With the number of sales channels available to firms increasing (see e.g., Marketing Science Institute 2018-2020), firms can reach more consumers and provide consumers with more convenience. However, the additional sales channels also increase complexity with multichannel management. Prior (industry) studies posit that a multichannel strategy is more effective based on findings supporting the general notion that a multichannel customer (in comparison to a single channel customer) is more profitable (e.g., Montaguti, Neslin, and Valentini, 2016; Kumar, Bezawada, and Trivedi, 2018). Based on this, we also see firms adding

more sales channels although only one third of the marketing managers reports to feel confident in being able to deliver a promising multichannel strategy (CMO, 2015). Hence, more precise understanding about multichannel effectiveness is required. Currently, studies do not provide insights into multichannel behavior effectiveness for firms offering multiple brands (i.e., multi-brand firms) although many multi-brand firms can be found in different industries (e.g., travel & hospitality industry, the finance industry, the FMCG industry, and the car industry). Furthermore, insights into multichannel behavior effectiveness when considering customer heterogeneity (e.g., on loyalty status) are lacking. To provide insights into these understudied issues, we assess the moderating effects of brand tier and customer loyalty tier on the relation between multichannel behavior and purchase outcomes. Overall, the results indicate that multichannel customers (vs. single channel customers) generate more revenue. In contrast to conventional wisdom and prior literature, we show that this is not always the case. Single channel customers generate more revenue for the highest-level loyalty tier and specific combinations of highest-level loyalty tier and brand tiers. The results have implications for both theory and managerial practice, which we will provide in the following.

3.8.1. Theoretical implications

We contribute to the literature in several ways. First, we extend prior research on the effects of multichannel customers (e.g., Kushwaha and Shankar, 2013) by offering new insights into the moderating effects of brand tier. Currently, most multichannel studies focus on a single brand, despite the fact that many firms offer multiple brands within and across multiple product (and/or service) categories (i.e., multi-brand firms; see Ambler et al., 2002). In line with prior research investigating the effect of multichannel customers on purchase behavior (e.g., Montaguti, Neslin, and Valentini, 2016; Kumar, Bezawada, and Trivedi, 2018), the results show that multichannel customers (vs. single channel customers) generate more revenue across all brands. Our findings confirm research by Verhoef, Langerak, and Donkers (2007), who

study the moderating role of brand tier for retention (brand and dealer) in the car industry and find differences for economy, volume, and prestige brand tiers. This finding is also in line with our hypothesis as the positive multichannel effect is smaller for the higher-tier and lower-tier brands.

Second, we also extend prior research on the effects of multichannel behavior (e.g., Kumar, Bezawada, and Trivedi, 2018) by offering new insights into the moderating effects of customer loyalty tier. In contrast to conventional wisdom and prior literature, we show that multichannel customers do not always generate more revenue. Results indicate that a *decreasing* intensity of multichannel usage by higher loyalty tier customers is associated with *increasing* customer spending. In other words, single channel customers generate more revenue for the highest loyalty tier. This result is in line with research by Konus, Verhoef and Neslin (2008) and our hypothesis.

An additional explanation for this finding might be that more loyal customers (i.e., higher loyalty tier, implying more bookings and/or higher priced bookings) expect higher service levels, such as preferential treatment (e.g., Gwinner, Gremler, and Bitner, 1998). To provide this higher service level to these customers, firms are only able to use their owned channels, which implies using the firm-owned channels (e.g., by phone, web, app, or in person). Thereby, the highest level of (personal) service is expected to only be found in specific channels, which consequently should lead to higher revenue outcomes. In order to confirm this, we conducted exploratory analyses (e.g., independent samples t-test) where we investigate which type of channels work best among this type of customers.

When comparing firm-owned vs. partner-owned channel types, we find that partner-owned channels have higher revenue per stay for all loyalty tiers except loyalty tier 4 where the difference is not significant (LT1: $M_{\text{firm-owned}} = 183.85$, $M_{\text{partner-owned}} = 224.52$, $p < .001$; LT2: $M_{\text{firm-owned}} = 196.56$, $M_{\text{partner-owned}} = 234.75$, $p < .001$; LT3: $M_{\text{firm-owned}} = 206.86$, $M_{\text{partner-owned}} = 251.34$, p

$< .001$; LT4: $M_{\text{firm-owned}} = 219.63$, $M_{\text{partner-owned}} = 228.19$, $p = .41$). This means that the average revenue per stay for customers residing in loyalty tier 4 (i.e., most loyal customers) does not differ between partner-owned and firm-owned channels. Furthermore, we investigated whether loyalty tier 4 customers use online or offline firm-owned channels across all brand tiers by conducting a simple regression (see appendix 3.B). Initial results show that customers residing in loyalty tier 4 and using firm-owned channels have a higher average revenue per stay across all brands when using online channels ($\beta = 17.38$, $p < .001$). However, this is not the case when these customers purchase brand tier D ($\beta = -89.96$, $p < .001$). In that case, the offline firm-owned channels have a higher revenue per stay (compared to online firm-owned channels). This result suggests that higher loyalty tier customers purchasing the highest tier brand (i.e., brand D) are most valuable when they turn to offline firm-owned channels.

Bringing the previous two contributions together, we also extend prior research on the effects of multichannel customers by exploring the moderating effects of brand tier and customer loyalty tier together (i.e., three-way interactions). This enables us to provide a first peek into the effectiveness of multichannel (vs. single channel) customers across the different brand-loyalty tier combinations. In line with our other results, we find that higher brand-loyalty tier combination customers generate more revenue when using a single channel (or very low number of channels). The same explanation as with the moderating effect of customer loyalty tier could also apply here. Customers with a higher loyalty tier prefer more service and this is especially the case when purchasing at a higher tier brand.

Lastly, we extend the customer management literature as well as the loyalty program literature. We consider the interface between brand management and customer management. Most customer management studies do not take potential differences between brand(s) (tier(s)) into account, but rather investigate how their customer management practices influence loyalty and purchase behavior. Nevertheless, Ambler et al. (2002) and Leone et al. (2006) already

acknowledge the importance of taking the interface between customer management and brand management into account as both represent two sides of the same coin. Considering one without the other is unlikely to be as effective whereas the combination of both will most often be greater in effectiveness than either alone. Thereby, customer and brand management together can help to improve the marketing success of a firm (Ambler et al., 2002; Leone et al., 2007). With regard to the loyalty program literature, most studies focus on the effects of loyalty tiers on behavior (e.g., Kopalle et al., 2012; Drèze and Nunes, 2011). However, they do not consider multichannel behavior and brand tiers, although firms frequently use multiple sales channels and many firms offer multiple brands.

3.8.2. *Managerial implications*

Our results have important implications for firms (see table 3.8 for an overview of our results and their implications). Marketing managers can make use of our results to gain more understanding on multichannel effectiveness and apply this in their firm. In particular, multi-brand firms (offering multiple brands within and across multiple product and/or service categories) and/or firms segmenting their customers based on loyalty status (e.g., using loyalty programs) can benefit from our results by learning from our insights how to manage multichannel customer behavior – that is, whether all customers should be multichannel.

First, marketing managers can use the findings on our main effect between multichannel customers and revenue outcomes to help with investment decisions for channels. In general, the results reveal that multichannel customers (vs. single channel customers) generate more revenue. This result remains when considering multiple brand tiers. Therefore, firms with multiple brands can invest in their channels in order to stimulate customers to use multiple sales channels. For example, a firm could invite a (new) customer that booked via (online) travel agent to book via the firm-owned channels by providing a gift during their stay or a discount. This might prompt the customer to book again and use another channel this time.

Despite the general finding of multichannel customers being most valuable, managers should note our findings on the moderating effect of customer loyalty tiers. Findings show that customers in highest loyalty tiers (i.e., most loyal customers) generate more revenue when using a single sales channel. In comparison with the lowest loyalty tier, which is also the loyalty tier for new customers, more loyal customers are more valuable when using a single channel. This is, potentially, driven by the need for (personal) service of these customers. Therefore, highest loyalty tier customers should be allowed to choose a single sales channel and not be driven or forced towards multiple sales channels. With regard to the type of channel these single channel customers prefer, initial results indicate that the revenue for these customers do not differ between partner-owned and firm-owned channels, which implies that customers could be turned to the channels where the best service can be provided and where revenue may potentially be higher (i.e., firm-owned channels). Furthermore, an exploratory analysis shows that the revenue per stay for this type of customer – loyalty tier 4 customer purchasing via firm-owned channels – is highest for offline channels when purchasing brand tier D. These offline firm-owned channels are rather costly for firms (e.g., phone lines), but we suggest that these costly sales channels should not be discarded for these customers. For future innovation in channels, firms might consider developing apps or online channels that are customized for these high loyalty tier/high brand tier customers. It may be that the personal, customizable aspect of the firm-owned, offline channel (i.e., phone) may be able to be replicated in a less costly, automated channel.

Third, we explored whether multichannel customers (vs. single channel customers) are more valuable for all brand-loyalty tier combinations. In line with the results for the moderating effect of loyalty tier, initial results show that this is not the case. Our results show that single channel customers are more valuable for the combinations of highest loyalty tier and brand tiers. This effect becomes more pronounced when higher loyalty tier customers purchase at a

higher tier brand. Therefore, high loyalty tier customers purchasing at higher tier brands (i.e., upscale and luxury brands) should also be allowed to use their preferred single channel.

In sum, we suggest marketing managers to consider their customers based on their purchased brand tiers and loyalty status in order to determine what strategy to apply. Overall, we find that new customers (with the lowest loyalty tier) prefer to use multiple sales channels across all brands. However, if the customers become more loyal (and purchase more frequently), they should be allowed to use a single channel (even if costly to the firm) and should not be incentivized to use multiple sales channels. By applying this strategy, the customers will be most valuable for the firm and both parties gain most.

Table 3.8: Managerial table of results

	Finding	Managerial implication
Main effect	Overall, multichannel customers (vs. single channel customers) generate more revenue	<ul style="list-style-type: none"> ▪ Firms (with multiple brands) can invest in their channels in order to stimulate customers to use multiple sales channels.
Interaction multichannel and brand tier	Across all brand tiers, multichannel customers (vs. single channel customers) generate more revenue	
Interaction multichannel and loyalty tier	In comparison with the lowest loyalty tier, customers in highest loyalty tiers (i.e., most loyal customers) are more valuable when using a single channel.	<ul style="list-style-type: none"> ▪ Newly acquired customers (with the lowest loyalty tier) prefer to use multiple sales channels across all brands. ▪ Highest loyalty tier customers should be allowed to choose a single sales channel and not be driven or forced towards multiple sales channels.
Interaction multichannel, brand tier and loyalty tier	Single channel customers are more valuable for the combinations of highest loyalty tier and brand tiers customers. An exploratory analysis shows that the revenue per stay for customer in the highest loyalty tier purchasing the highest brand tier (luxury brand) is highest for offline channels.	<ul style="list-style-type: none"> ▪ Despite offline firm-owned channels being rather costly for firms, these costly sales channels should not be discarded for this type of customer. ▪ For future innovation in channels, firms might consider developing online channels that are customized for these high loyalty tier/high brand tier customers. Potentially, the personal, customizable aspect of the firm-owned, offline channel can be replicated in a less costly, automated channel.

3.8.3. *Limitations and further research*

We acknowledge some limitations of our research that also provide opportunities for interesting future research. In particular, though we find occasions when single channel users generate more revenue (compared to multichannel users), we do not provide research on what specific channels work best in these cases. We made a first attempt to explore this, but future research can continue by investigating which type of sales channels (e.g., online vs offline and/or firm-owned vs partner-owned) contributes optimally to revenue for which brand tier and/or loyalty tier.

Our study examined observed purchase behavior. We do not have data on how customers use the available channels in the pre-purchase stage. Although the data is hard to collect, analyzing pre-purchase stage data together with the transactional data could provide more understanding on multichannel shopping.

Another avenue for research will be to study possible differences among various types of consumers, according to their distinct consumer responses and demographic information. As an example, considering RFMC segmentation to segment customers and investigate whether RFMC tiers matter. In our study, the data did not include demographic information and thereby we were also not able to distinguish individual consumers based on this information.

Additionally, our study refers to a single, travel industry firm. Though the travel industry is substantive and studied frequently (e.g., Ou, Verhoef, and Wiesel, 2017; Rust, Lemon, and Zeithaml, 2004), we acknowledge that other industries use a multichannel strategy and rely on their effects on purchase behavior. Therefore, our study could be generalized in other industries. This also applies to other product categories. Investigating the impact of multichannel behavior on category sales in addition to brand sales would then also be interesting to look into.

Finally, there will be significant new opportunities for research post-pandemic as firms seek to understand how consumers re-engage with industries such as travel and hospitality in this

new world. Given the rise of digital during this time, future research should examine consumer preferences for distinct channels, brand tiers and loyalty programs – and seek to understand how their purchase journeys and purchase decisions have changed as a result of the pandemic.

3.8.4. Conclusion

Existing studies support the (general) notion that a multichannel customer (compared to a single channel customer) is more profitable and thereby a multichannel strategy is more effective. However, current studies do not consider what happens to multichannel effectiveness when (1) a firm offers multiple brands (i.e., multi-brand firm), and (2) customer heterogeneity (on loyalty status) is considered. To provide insights into these prevailing issues, we study whether multichannel vs. single channel customers are always more valuable by studying multichannel effectiveness across brands and customer loyalty tiers. Overall, the results indicate that multichannel customers generate more revenue, but this is not always the case. Single channel customers (vs. multichannel customers) generate more revenue for the highest-level loyalty tier and combinations of highest-level loyalty tier and brand tiers. Our results also suggest that firms should not “force” all customers into being multichannel; rather a more nuanced approach that accounts for brand and loyalty tiers may yield better revenue results. With these results, we strive to provide insights to firms that help them to getting a deeper understanding of the effectiveness of multichannel customer behavior, and to develop a multichannel strategy to grow revenue. Thereby, we enable firms to gain the most value from and provide the most value to their customers.

Appendix 3.A: Descriptives and correlation table

Table 3.A.1: Descriptives and correlation table

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Revenue	197.10	183.15	1.00 (1.00)														
2	Duration of stay	1.65	1.23	.80 (0.00)	1.00 (1.00)													
3	MCSI	0.36	0.22	.03 (0.00)	.02 (0.00)	1.00 (1.00)												
4	Brand tier purchased	1.34	X	.17 (0.00)	.08 (0.00)	.04 (0.00)	1.00 (1.00)											
5	Loyalty tier	2.02	X	.05 (0.00)	.07 (0.00)	.02 (0.00)	.01 (0.00)	1.00 (1.00)										
6	Recency	49.57	71.74	.10 (0.00)	.07 (0.00)	-.04 (0.00)	.06 (0.00)	-.31 (0.00)	1.00 (1.00)									
7	Frequency	28.16	27.54	-.12 (0.00)	-.09 (0.00)	-.07 (0.00)	-.05 (0.00)	.65 (0.00)	-.33 (0.00)	1.00 (1.00)								
8	Avg spend before	200.50	106.63	.39 (0.00)	.32 (0.00)	.07 (0.00)	.19 (0.00)	.17 (0.00)	.13 (0.00)	-.21 (0.00)	1.00 (1.00)							
9	Home region	0.05	X	.10 (0.00)	.08 (0.00)	.01 (0.00)	.22 (0.00)	-.01 (0.00)	.04 (0.00)	-.06 (0.00)	.13 (0.00)	1.00 (1.00)						
10	Corporate rate	0.18	X	.01 (0.00)	.08 (0.00)	-.01 (0.00)	.05 (0.00)	.09 (0.00)	-.06 (0.00)	.09 (0.00)	-.01 (0.00)	.02 (0.00)	1.00 (1.00)					
11	Dom brand	1.20	X	.12 (0.00)	.06 (0.00)	.00 (0.00)	.54 (0.00)	-.01 (0.00)	.08 (0.00)	-.09 (0.00)	.24 (0.00)	.19 (0.00)	.07 (0.00)	1.00 (1.00)				
12	Bonus point package use	0.04	X	.02 (0.00)	-.02 (0.00)	.04 (0.00)	-.01 (0.00)	.10 (0.00)	-.03 (0.00)	.04 (0.00)	.02 (0.00)	-.01 (0.00)	-.07 (0.00)	-.02 (0.00)	1.00 (1.00)			
13	Free night voucher use	0.00	X	.00 (0.00)	.00 (0.08)	.00 (0.02)	.00 (0.01)	.00 (0.21)	.00 (0.07)	.00 (0.00)	.00 (0.03)	.00 (0.73)	.00 (0.01)	.00 (0.99)	.00 (0.23)	1.00 (1.00)		
14	Redeeming points	0.07	X	-.18 (0.00)	-.07 (0.00)	.03 (0.00)	.01 (0.00)	.05 (0.00)	.02 (0.00)	.00 (0.00)	.05 (0.00)	-.01 (0.00)	-.13 (0.00)	-.01 (0.00)	-.05 (0.00)	.00 (0.11)	1.00 (1.00)	
15	Region key	X	X	.01 (0.00)	.03 (0.00)	.02 (0.00)	.10 (0.00)	.00 (0.00)	.01 (0.00)	-.02 (0.00)	.01 (0.00)	.15 (0.00)	.04 (0.00)	.10 (0.00)	.00 (0.01)	.00 (0.95)	.00 (0.16)	1.00 (1.00)

Appendix 3.B: Results of the control variables and exploratory analysis

Table 3.B.1: Results control variables

	Model 1		Model 2		Model 3		Model 4		After PSM Model 5
<i>Controls</i>									
Recency		0.00 ***		0.00 ***		0.00 ***		0.00 ***	
Frequency		-0.00 ***		-0.00 ***		-0.00 ***		-0.00 ***	
Avg spending before		0.00 ***		0.00 ***		0.00 ***		0.00 ***	
Home region		0.06 ***		0.06 ***		0.06 ***		0.06 ***	
Corporate rate		-0.02 ***		-0.02 ***		-0.02 ***		-0.01 ***	
Dom brand B		-0.04 ***		-0.04 ***		-0.04 ***		-0.03 ***	
Dom brand C		-0.12 ***		-0.11 ***		-0.11 ***		-0.11 ***	
Dom brand D		-0.38 ***		-0.36 ***		-0.36 ***		-0.36 ***	
Bonus point package rate		0.05 ***		0.05 ***		0.05 ***		0.05 ***	
Free night voucher use		-1.22 ***		-1.22 ***		-1.22 ***		-1.24 ***	
Redeeming points		-1.35 ***		-1.35 ***		-1.35 ***		-1.38 ***	
Region key		-0.02 ***		-0.02 ***		-0.02 ***		-0.02 ***	
Channel pref cro		0.00		0.00		0.00		0.00	
Channel pref gds		0.03 ***		0.02 ***		0.03 ***		0.03 ***	
Channel pref htl		-0.03 ***		-0.03 ***		-0.03 ***		-0.02 ***	
Channel pref ota		0.03		0.02		0.02		0.03	
Channel pref oth		0.04 ***		0.03 **		0.03 **		0.02	
Channel pref web		0.04 ***		0.04 ***		0.04 ***		0.04 ***	

.*p* < .10; * *p* < .05; ** *p* < .01; *** *p* < .001

Table 3.B.2: Results exploratory analysis

	Estimates	
Intercept	198.89	***
Brand B	9.54	**
Brand C	70.11	***
Brand D	361.62	***
Online	17.38	***
Brand B * Online	1.54	
Brand C * Online	10.29	
Brand D * Online	-89.96	***

Note: this analysis only considers loyalty tier 4 customers purchasing through firm-owned channels

.*p* < .10; * *p* < .05; ** *p* < .01; *** *p* < .001

Appendix 3.C: Robustness checks

Table 3.C.1: Main results robustness check

	Main model		Aggregate data		Binary variable multi vs single		Weekend nights		Customer specific variables		DV = # nights		Incl. registered customers	
Main effects														
MCSI	+	***	+	***	+	***	+	***	+	***	+	*	+	***
Brand B	+	***	+	***	+	***	+	***	+	**	+	***	+	***
Brand C	+	***	+	***	+	***	+	***	-	.	+	***	+	***
Brand D	+	***	+	***	+	***	+	***	+	***	+	***	+	***
Loyalty tier 2 (LT 2)	+	***	+	***	+	***	+	***	+	***	+	***	+	***
Loyalty tier 3 (LT 3)	+	***	+	***	+	***	+	***	+	***	+	***	+	***
Loyalty tier 4 (LT 4)	+	***	+	***	+	***	+	***	+	***	+	***	+	***
Interaction effects														
Brand B*MCSI	n.s.		-	*	n.s.		n.s.		n.s.		n.s.		n.s.	
Brand C*MCSI	+	***	+	**	+	***	+	***	+	***	+	*	+	***
Brand D*MCSI	n.s.		-	***	n.s.		n.s.		n.s.		n.s.		n.s.	
LT2*MCSI	-	***	-	***	-	*	-	***	-	***	-	.	-	***
LT3*MCSI	-	***	n.s.		n.s.		-	***	-	***	-	**	-	***
LT4*MCSI	-	***	-	**	-	***	-	***	-	***	-	***	-	***

. $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

Chapter 4

Discussion

This dissertation focuses on two of the challenges marketing faces in the digital era: (1) management of different (online and offline) communication channels, and (2) management of different distribution channels. With the advent of digital technologies and ongoing digitalization, new channels – for communication as well as distribution – have proliferated and this has affected business models, marketing strategies, and consumer behavior (e.g., Kannan and Li, 2017; Verhoef and Bijmolt, 2019). The general aim of this dissertation is to gain a better understanding how to deal with these prominent challenges that emerge when online meets offline.

Our knowledge on the effectiveness on traditional marketing communication in the new digital world is scarce (e.g., Marketing Science Institute 2018-2020). Hence, we study the effect of a frequently applied traditional marketing communication tool, direct mailing, and how it affects online consumer responses (see Chapter 2). Furthermore, with new marketing communication media, insights into how these interact with traditional marketing communication tools – whether they complement or substitute one another – is very limited. Thus, we also study the potential synergy between direct mailing and display advertising (see Chapter 2). By answering both research questions in two studies, we provide evidence that direct mailing still serves as an effective marketing tool – by itself and in combination with digital marketing – despite the rise of digital media.

Understanding on whether it is most beneficial for firms when their customers are multichannel (compared to single channel) and thereby how to develop a promising multichannel strategy is not complete (e.g., Liu, Lobschat and Verhoef, 2018). Current research does not study the effects of multiple brands (i.e., multi-brand firm) or customer heterogeneity in loyalty status on multichannel effectiveness. However, many firms offer multiple brands within and across multiple product (and/or service) categories (e.g., in industries like the travel & hospitality, finance, FMCG, and car industry). Also, the effects of marketing and channel

strategies are found to differ between different types of customers (i.e., customer heterogeneity) as well as loyalty programs being applied frequently by firms. Therefore, we investigate whether customers should be multichannel by considering whether the effect of multichannel shopping on consumers' purchase behavior differs across different brand and loyalty tiers (see Chapter 3). By answering this question, we present insights for firms by showing that a multichannel strategy pays out in most cases, but not always. Boundary conditions need to be taken into account in order to best serve all different types of customers across the different offered brand tiers. In this final chapter of the dissertation, we summarize our findings, provide managerial implications, and propose future research directions.

4.1. Main findings and managerial implications

In this section, we highlight the main findings from our two empirical studies and provide implications for marketing managers.

4.1.1. Chapter 2: Do offline and online go hand in hand? Cross-channel and synergy effects of direct mailing and display advertising

In today's digital media age, questions remain how direct mailing affects consumers' online (and offline) activity metrics throughout the purchase funnel and how direct mailing interacts with digital marketing tools. To provide insights into these prevailing research questions, we conducted two studies in chapter 2. In the first study, we assess the impact of a direct mailing campaign on different upper, middle, and lower online (and offline) performance metrics, using quasi-experimental data on the zip code level from an international insurance firm. The results indicate that direct mailing exerts effects on all stages of the purchase funnel. We find significant cross-channel effects on consumers' online search and clicking behavior which – in combination with the positive impact on the number of purchases – provide evidence for an indirect (sales) effect of direct mailings. Using data from a follow-up field experiment with the same insurance firm, the second study investigates the potential synergy effects of direct

mailing and display advertising. Furthermore, the field experiment data enables us to gain more confidence in the results of study 1. The results indicate that direct mailing yields a lift in the number of purchases on its own and together with display advertising. Moreover, we find support for a synergy effect between direct mailing and display advertising.

These results have important implications for firms that currently use, or are planning to use, direct mailing. In our empirical application, we confirm that this traditional marketing tool remains effective even in the digital media environment; it is “far from dead” (*Forbes*, 2017). In the financial services industry – representing the heaviest users of direct mailing (DMA, 2018) – firms can benefit from this tactic. Our results provide supportive evidence that direct mailing is still a viable marketing tool, given their direct and indirect impact on consumers’ purchase behavior and synergy with display advertising. Apart from this, our results have implications for attribution modeling, managing a direct mailing campaign over time, and the integration of other (digital) marketing activities, which we outline next.

For attribution modeling implications, our results indicating effects on upper and middle purchase funnel stages suggest firms to assign value to direct mailing beyond just looking at the last action. When simply looking at the number of purchases as the only key performance indicator of a direct mailing campaign, marketing managers might underestimate its overall effectiveness. Given the relatively high costs associated with running a direct marketing campaign, marketing managers should consider also using the indirect effect associated with guiding consumers through the purchase funnel to justify their direct mailing budgets to the C-suite within the firm. Furthermore, our results suggest that the effects of direct mailing across the different purchase funnel stages change considerably over time. For managing a direct mailing campaign over time, marketing managers might consider supporting consumers’ decision for the focal brand by running e.g., TV ads (or the alike) during these time periods. Marketing managers should also consider allocating sufficient support staff to promising

periods to the online channel (e.g., in the form of online chat personnel, and inform their agencies accordingly) given that our focal product is consultation-intensive.

For the integration of other digital marketing activities, managers could consider the set-up of their direct mail. Our results suggest that the brand could be integrated more prominently to avoid consumers to look for alternative brands. Furthermore, firms could potentially integrate a QR code (or something alike) to the focal firm's website to direct the consumer to their website immediately and thereby provide easier access to the online offering. We also find positive synergy between direct mailing and display advertising. Hence, marketing managers could contemplate using direct mails in combination with digital marketing instruments. When integrating marketing communication tools, potential synergy should be considered in order to gain the most. As synergy arises and increases, Naik and Raman (2003) find support that the advertiser should increase (decrease) the proportion of media budget allocated to the less (more) effective communications activity. Also, marketing managers should take into account how to effectively integrate other digital marketing activities when planning a direct mailing campaign.

4.1.2. Chapter 3: Should all customers be multichannel? Investigating the moderating role of brand and loyalty tier

Existing studies have not unpacked what happens to multichannel effectiveness when (1) a firm offers multiple brands (i.e., multi-brand firm), and (2) when considering customer heterogeneity (on loyalty status). To provide insights into these prevailing issues, chapter 3 of this dissertation studies discusses whether multichannel customers are more valuable than single channel customers by studying multichannel effectiveness across brand and customer loyalty tiers. Overall, the results indicate that a multichannel strategy is more effective with multichannel customers generating more revenue compared to single channel customers, in line with prior research (e.g., Ansari, Mela and Neslin, 2008; Montaguti et al., 2016). Nevertheless, this is not always the case. Single channel customers generate more revenue for the highest-

level loyalty tier and combinations of highest-level loyalty and brand tiers. With our findings, we aim to provide firms with a precise understanding of the effectiveness of multichannel marketing in the context of multiple brands and taking into account consumer heterogeneity, and to help with developing a promising multichannel strategy to grow revenue. Thereby, firms are enabled to provide the most value to and to gain the most value from their customers.

The results presented in chapter 3 have important implications for firms. Marketing managers can make use of our results for a better understanding of multichannel effectiveness in order to apply this in their firm. This is especially the case for firms offering multiple brands within and across multiple product and/or service categories (see Ambler et al., 2002) as well as firms segmenting their customers based on loyalty status (e.g., with a loyalty program). These types of firms can benefit from our findings as we provide them with an indication when it helps to promote multichannel behavior and when not, but also how to develop a promising multichannel strategy – that is, whether all customers should be multichannel.

Marketing managers can use our main effect result indicating multichannel behavior to be more valuable as guidance with investment decisions for channels. Our findings show that multichannel customers generate more revenue across all brand tiers. Hence, for multi-brand firms it might be beneficial to invest in their channels in order to stimulate customers to use multiple sales channels. Nonetheless, firms should be aware of our findings on the moderating effect of customer loyalty tiers. We show in our context that the most loyal customers (i.e., highest loyalty tier customers) generate more revenue when using a single sales channel. For that reason, highest loyalty tier customers should be allowed to choose a single sales channel and not be driven towards multiple sales channels (e.g., by delivering marketing communication to them). With regard to the type of channel these single channel customers prefer, initial results show that the revenue per stay for this type of customer (using firm-owned channels) is highest for offline channels when purchasing the highest brand tier. These offline

firm-owned channels are rather costly for firms. However, we suggest that these costly sales channels should not be discarded for this type of customers (i.e., most loyal customers buying high tier brands). For future innovation in channels, firms might even consider developing online channels (e.g., apps) that are customized for these most loyal customers purchasing high brand tiers. It may be that the personal, customizable aspect of the firm-owned, offline channel (i.e., phone) may be able to be replicated in a less costly, automated channel.

Overall, our research suggests marketing managers to take a more nuanced approach that accounts for consumers' purchased brand tiers and loyalty status in order to determine their multichannel strategy. Thereby, the customers will be most valuable for the firm and both parties gain most.

4.2. Future research directions

In this dissertation, we conduct research on challenges for marketing in the digital era from two different perspectives – communication and distribution – and provide useful insights for both theory and practice. For both challenges we investigate, we have identified opportunities for future research in order to continue improving our understanding, which we discuss in this final section of this chapter.

4.2.1. Future research opportunities based on chapter 2

Chapter 2 studies the effectiveness of direct mailing in the online environment (i.e., cross-channel effects) and secondly, explores whether there is synergy between direct mailing and a digital marketing communication tool (i.e., display advertising). Insights in these key questions can help marketing managers to face the challenges for marketing communication channels in a digital era. In order to advance towards an even better understanding on this challenge for marketing communication, we identify future research avenues.

First of all, future research could explore the treatment effect of direct mailing – by itself or in combination with other (digital) marketing communication tools – at the individual level.

We make use of aggregate level (zip code level) data to study the effect of direct mailing on multiple consumer responses throughout the purchase funnel. However, actual purchase funnel progression arises on the individual customer level. The digital era enables researchers to retrieve more data on the individual consumer level (e.g., Leeflang et al., 2014). This data could help to track consumers in their path to purchase and analyze the treatment effect of direct mailing in this path – by itself or in combination with other (digital) marketing communication tools. The individual level data can also rule out potential cofounds arising with aggregate data. Hence, allowing for more profound information on the underlying process of the cross-channel and synergy effects to be retrieved. Furthermore, data on the individual consumers facilitates the use of demographical information on the individual consumer in future research. This enables future work to see whether the consumer responses to direct mailing differ for different consumer segments. Research shows that different customer segments respond differently (e.g., Konus, Verhoef and Neslin, 2008; Herhausen et al. 2019), but it would be interesting for future research to look into this for direct mailing in combination with other (digital) marketing communication. This will help marketing managers to target (segments of) consumers with the right marketing communication.

Another direction for future research on direct mailings (offline marketing communication instrument) in the digital era is to study the impact when integrating digital and offline marketing activities. When integrating digital marketing options in the direct mail this enables firms to track the response to the direct mail. For example, when a personal link or QR code to the online web shop is provided on the direct mail, this allows firms to track the usage of this offline marketing communication tool together with potential subsequent online consumer activity. Thereby, the effectiveness of this marketing communication can be measured more accurately. More specifically with respect to the design of the direct mailing, we suggest that the design of the direct mailing in our first study might explain that the product category was

put top-of-mind of consumers, but not the focal brand. Design characteristics, therefore, impact the performance of the direct mailing, in line with prior research (e.g., Feld et al., 2013). Future research could take this into account and consider multiple designs of direct mailings and its effects throughout the purchase funnel as well as in combination with other (digital) marketing communication. Lastly, future research could extend our research to other offline marketing communication instruments (e.g., print advertising or catalogues). These other offline marketing communication channels could replace direct mailing or be studied in addition to direct mailing to see its effectiveness throughout the purchase funnel (in the digital era), but also in combination to digital communication.

4.2.2. Future research opportunities based on chapter 3

Chapter 3 examines whether customers using multiple sales channels always generate more revenue than customers using a single sales channel by investigating the multichannel effectiveness across brands and customer loyalty tiers. With these insights, we strive to help firms to getting a deeper understanding of the effectiveness of multichannel marketing, and to developing a multichannel strategy to grow revenue. This allows them to gain the most value from and provide the most value to their customers. Based on our research, we have recognized opportunities for future research, which we outline in the following.

Firstly, future research could focus on the stages preceding the actual purchase, and the channels used in those stages. Our study centers around the sales channels available to consumers. However, before consumers actually conduct a purchase, they might already have interacted with the firm across multiple channels. Building on the research by Gensler, Verhoef and Böhm (2012), future research could take into account not only the sales stage, but also their channel usage in other stages of the purchase process. For example, a customer might have searched for information on the firm through a channel (i.e., search engine or digital platform)

and eventually conducted their purchase through the website of the firm. These insights would provide firms guidance on developing and applying the most beneficial multichannel strategy.

Also, future research could broaden the scope to other industries. In our study, we focus on a single industry, the travel industry, and single hotel group to study the moderating effects of multiple brands and customer heterogeneity. However, loyalty programs are also used in other industries. Similarly, multi-brand firms are also present in other industries (e.g., car or FMCG industry). In the different industries, differences in multichannel effectiveness and the effects of our moderators might appear due to, for example, the type of products and/or services that are offered in these industries and associated type of buying behaviors (Kotler and Armstrong, 2018). For example, in the car industry consumers are highly involved (based on the expensive product and they purchase this infrequently) and there are significant differences between brands, which implies complex buying behavior (Kotler and Armstrong, 2018). For FMCG industry, there is low consumer involvement and there might still be significant differences between brands leading to variety-seeking buying behaviors (Kotler and Armstrong, 2018). These different buying behaviors might lead to differences in multichannel effectiveness as well as differential effects of the moderators. This is interesting for future research to look into.

Another fruitful future research opportunity is to look into channel selection and which type of channels contribute most in a multichannel or single channel strategy (by the brand or customer). In our study, we are not able to fully take into account the type of sales channel(s) used by the customer. We conducted an exploratory analyses to provide information on which specific type of channel works best for which type of customers, however, future research could focus on investigating which type of channels (e.g., online or offline and/or firm-owned or partner-owned) provides the most value in which context and/or for which type of customer. This would provide guidance to firms on what channels to apply when and for which customers.

Related to the previous recommendation, multichannel strategies are replaced by omnichannel strategies (Verhoef, Kannan and Inman, 2015). The different channels “are interchangeably and seamlessly used during the search and purchase process and it is difficult or virtually impossible for firms to control this usage” (Verhoef, Kannan, and Inman, 2015, p. 175). Future research could look into which type of channels or specific channels complement each other in which stage of the purchase funnel as well as for which type of consumer. This also builds on our research in chapter 2 by providing firms with insights how to integrate different channels in order for their customers to have the best experience. Thereby, the firm provides the best value and gains the most value from their customers.

Finally, we have a future research opportunity bringing our two studies together. In our first empirical study (chapter 2), we study how marketing communication influences consumer behavior. In chapter 3, we show whether a multichannel (vs. single channel) customer generates more revenue while considering multiple brands and customer loyalty status and provide suggestions for multichannel strategies. Integrating these studies and building on Montaguti, Neslin and Valentini (2016), future research could study how marketing communication (offline or online) can be used to influence consumer decisions, such as decisions on which sales channel to use. Consequently, research can investigate how this differs across the different brand tiers and customer segments (e.g., customer loyalty tiers). These insights are also helpful with our other future research suggestions as suggested above. When we have more understanding on what type of channels work best in which context, firms can use these insights into how to influence customers into using these channels. Altogether, it is almost impossible to imagine living *without* being digital nowadays, however, the question remains whether we know how to live *with* the digital technologies?

Chapter 5

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Chapter 6

Nederlandse Samenvatting

Tegenwoordig is het bijna onmogelijk ons leven voor te stellen *zonder* digitale technologieën, terwijl het 25 jaar geleden nog haast onmogelijk was ons leven voor te stellen *met* deze digitale technologieën. Dit proefschrift focust op twee uitdagingen voor marketing in het digitale tijdperk: (1) het management van verschillende (online en offline) communicatiekanalen, en (2) het management van verschillende distributie (verkoop) kanalen. Door de opkomst van digitale technologieën en de bijbehorende digitalisering zijn nieuwe kanalen (voor zowel communicatie als verkoop) in een hoog tempo ontstaan. Deze opkomst van nieuwe kanalen heeft sterke invloed gehad op businessmodellen, marketingstrategieën en consumentengedrag (e.g., Kannan en Li, 2017; Verhoef en Bijmolt, 2019). Het doel van dit proefschrift is om beter te begrijpen en onze kennis te verbreden met betrekking tot hoe om te gaan met deze twee uitdagingen voor marketing in de digitale wereld. Hoofdstuk 2 gaat in op de uitdaging van het managen van meerdere communicatiekanalen in dit digitale tijdperk. Om dit doel te bereiken, levert hoofdstuk 2 inzichten in de effectiviteit van een traditionele offline marketingcommunicatie instrument in de nieuwe digitale wereld. Daarnaast geeft dit hoofdstuk inzicht in de synergie tussen een traditioneel en digitaal marketingcommunicatie instrument. Hoofdstuk 3 richt zich op de uitdaging van het managen van verschillende verkoopkanalen door het onderzoeken van de vraag of alle consumenten multichannel zouden moeten zijn. In de volgende paragrafen worden deze twee empirische studies kort samengevat.

Hoofdstuk 2. Onze kennis en begrip over de effectiviteit van een traditionele marketingcommunicatie in de nieuwe digitale wereld is schaars (zie bijv. Marketing Science Institute 2018-2020). Zo zijn er beperkte inzichten in hoe online media samen met traditionele communicatiemedi consumenten beïnvloeden. Traditionele media blijven zeer belangrijk en veel bedrijven investeren nog in bijvoorbeeld tv- en radioreclame en maken gebruik van traditionele direct marketing, zoals direct mailings. Direct mailings zijn nog zeer relevant en worden veelvuldig toegepast. We weten echter niet hoe direct mailings het (online) gedrag van

consumenten beïnvloeden en hoe deze mailings werken in combinatie met nieuwe online media. Om deze vragen te onderzoeken, worden twee studies geïntroduceerd in hoofdstuk 2. In de eerste studie wordt het effect van een vaak toegepast traditioneel marketingcommunicatie instrument onderzocht, namelijk direct mailing, en wordt bekeken hoe dit instrument online klantreacties beïnvloedt. We richten ons op het effect van direct mailing op prestatie indicatoren voor verschillende fases in het koopproces, zoals online zoek-, klik- en koopgedrag. Hiervoor analyseren we quasi-experimentele data van een grote Europese verzekeringsmaatschappij op postcode niveau. Resultaten laten zien dat direct mailings een significante invloed hebben op klantreacties in digitale kanalen. Dit wijst op een zogenaamd cross-channel effect, het effect van offline op online. Naast het effect van direct mailings op online consumentengedrag, zoals zoekgedrag met zoekmachines, hebben ze ook direct invloed op het koopgedrag van consumenten. Het online consumentengedrag beïnvloedt ook het koopgedrag en daarmee hebben direct mailings niet alleen een direct maar ook een indirect effect op verkopen. Het totale effect (waarbij alle directe en indirecte effecten meegenomen worden) van direct mailings op verkopen is positief.

De tweede studie in hoofdstuk 2 onderzoekt hoe de combinatie tussen een traditioneel en digitaal marketingcommunicatie instrument consumentengedrag beïnvloedt – versterken of substitueren deze twee elkaar? Om deze vraag te beantwoorden bekijken we of er synergie is tussen direct mailing en display advertising, door het analyseren van data van een veldexperiment van dezelfde grote Europese verzekeringsmaatschappij. Onze bevindingen tonen een positieve synergie tussen de direct mailings en display advertising aan, waarmee we bewijs leveren dat deze instrumenten elkaar versterken en dat hun gezamenlijke effect groter is dan hun individuele effecten opgeteld. Door het beantwoorden van beide onderzoeksvragen in hoofdstuk 2 met behulp van bovengenoemde twee studies leveren we bewijs dat direct mailing nog steeds een effectief marketinginstrument is, ondanks de digitalisering. Dit geldt voor direct

mailing als een op zichzelf staand instrument, maar ook in combinatie met een digitaal marketingcommunicatie instrument.

Hoofdstuk 3. Het aantal verkoopkanalen dat beschikbaar is voor de consument neemt gestaag toe. Zo zijn de traditionele verkoopkanalen, zoals de fysieke winkels, uitgebreid met bijvoorbeeld webwinkels en apps. Het toepassen van meerdere verkoopkanalen, dat wil zeggen een multichannel strategie, biedt bedrijven de kans om consumenten beter te bereiken en tegelijkertijd biedt het consumenten meer gemak. Echter, dit verhoogt ook de complexiteit voor het beheren van de verschillende verkoopkanalen. Wanneer een consument meerdere verkoopkanalen gebruikt dan worden deze klanten ook wel bestempeld als multichannel. Het algemene beeld is dat multichannel klanten winstgevender zijn en dat daardoor een multichannel strategie effectiever is voor bedrijven. Echter, bestaande studies hebben nog niet bekeken wat er gebeurt met de multichannel effectiviteit wanneer (1) een bedrijf meerdere merken aanbiedt met een verschillende positionering (dat wil zeggen, een multi-brand firm), en (2) klantheterogeniteit in acht genomen wordt. Om hier inzichten in te leveren, onderzoeken we in hoofdstuk 3 of multichannel klanten waardevoller zijn in vergelijking met klanten die één verkoopkanaal gebruiken. De effectiviteit van multichannel klantgedrag bestuderen we voor verschillende merken en klanten die verschillen in loyaliteit, door het analyseren van een dataset met twaalf maanden data over het koopgedrag van een selectie klanten in het loyaliteitsprogramma van een grote internationale hotelgroep, Intercontinental Hotel Group (IHG). Onze resultaten laten zien dat multichannel klanten over het algemeen waardevoller zijn. Hierbij geven onze resultaten wel aan dat het positieve effect van multichannel klantgedrag op de omzet kleiner is voor laag- en hoog gepositioneerde merken in vergelijking met middel gepositioneerde merken. Echter, in tegenstelling tot het algemene beeld en resultaten van eerdere onderzoeken, zijn multichannel klanten niet altijd waardevoller. Onze bevindingen tonen aan dat klanten die één verkoopkanaal gebruiken meer omzet opleveren dan multichannel

klanten wanneer deze klanten zeer loyaal zijn, onafhankelijk van welk merk ze kopen. Met deze bevindingen streven we ernaar om bedrijven te voorzien van een helderder begrip van de effectiviteit van een multichannel strategie door rekening te houden met het dragen van meerdere merken en klantheterogeniteit. Hiermee hopen we bedrijven te kunnen helpen met het ontwikkelen van een omzet verhogende strategie. Al met al verhogen bedrijven hiermee de waarde *voor* en *door* hun klanten.

Dit proefschrift onderzoekt twee uitdagingen voor marketing in het digitale tijdperk, die naar voren zijn gekomen door de “ontmoeting van online en offline”: (1) hoe verschillende (online en offline) communicatiekanalen te beheren, en (2) hoe verschillende distributie (verkoop) kanalen te beheren. De hoofdstukken binnen dit proefschrift leveren nieuwe inzichten in deze uitdagingen om ons begrip te verbeteren en kennis uit te breiden. Ondanks dat marketing in het digitale tijdperk complex is met een grote variatie aan factoren die in wisselwerking met elkaar staan, hoop ik hierin een bijdrage te hebben geleverd met mijn proefschrift. Alles bij elkaar genomen, is het tegenwoordig vrijwel onmogelijk om ons een leven *zonder* digitale technologieën voor te stellen, maar de vraag blijft of we weten *hoe* we met deze digitale technologieën moeten leven.