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Should All Customers Be Multichannel? Investigating the Moderating Role of Brand and Loyalty Tier

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Abstract

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

Keywords: multichannel customer behavior, brands, loyalty programs, customer heterogeneity, customer management.

Introduction

The number of sales channels available to consumers is steadily growing (e.g., Marketing Science Institute 2018-2020). This offers firms the opportunity 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. single channel) strategy 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; 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 recent research priority of the Marketing Science Institute on managing distribution across channels (Marketing Science Institute 2020-2022) as well as by Van Bruggen et al. (2010). 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 categories (see Ambler et al. 2002). For example, in the airline industry, the Lufthansa Group comprises brands like Lufthansa, Brussels airlines, and Eurowings (among others). The different within-firm brands usually differ on service and/or price levels and serve as alternatives, although consumers can also buy multiple brands from the same firm (Kotler and Armstrong 2018). These multi-brand firms can be found in industries like travel & hospitality, finance (e.g., banking and insurance industries), auto, and FMCG (e.g., P&G). 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 modern marketing environments. 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) consumer 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 (Kopalle et al. 2012) as well as loyalty formation differing between customers segments (Herhausen et al. 2019). Thus, 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 firms as well as consumers' purchase likelihood (Liu 2007). Despite this, the moderating role of loyalty on the effect of customers' multichannel behavior on their revenue outcomes has not yet been considered. Hence, we propose that loyalty, in the interplay with customer brand choice among different brands and sales channels used, needs to be taken into account.

We also aim to contribute to the customer management and loyalty program literature. Most customer management studies investigate how 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, this approach is largely neglected in existing studies (e.g., Verhoef 2003), probably because it is difficult to obtain appropriate data. Nevertheless, when considering both customer and brand management, this can 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 Verhoef, Langerak, and Donkers (2007), who 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 channels or loyalty tiers. Most studies on loyalty programs focus on the effects of loyalty tiers on consumer purchase behavior (e.g., Kopalle et al. 2012; Drèze and Nunes 2011). However, differences in the effects of multichannel behavior between customers with different loyalty status have not been considered.

In sum, we investigate whether multichannel vs. single channel customer behavior generates more or less revenue by studying multichannel effectiveness across brand tiers and loyalty tiers. By investigating these research questions, we aim to provide more understanding on the effectiveness of the multichannel approach and thereby contribute to both theory and practice (see table 1 for our contribution relative to prior research). Additionally, we introduce the MultiChannel Share Index, which is a continuous measure on (the intensity of) multichannel behavior (see model development section) compared to the previously applied binary approach distinguishing between multichannel and single channel customers (e.g., Montaguti, Neslin, and Valentini 2016).

To study our research questions, 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. We also 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 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 the 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). 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 questions. Thereafter, we present the empirical results of our analyses and conclude with implications for research and practice.

---- Insert Table 1 about here ----

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 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). To study the effect of multichannel behavior, we develop the *MultiChannel 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 for each booked stay. 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 different brand tiers, consumers deem different attributes more (or less) 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 2 portrays how the brand tiers are positioned on these dimensions. The high brand tier (i.e., luxury tier) is classified as premium-priced and top-quality, ranking this brand tier at the top end of the market. The brand (image) of this 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 itself is of less importance with this brand tier as it is not purchased by consumers to communicate status, wealth, or exclusivity, but rather for utility reasons. Lastly, the low brand tier (i.e., economy tier) offers basic quality for the best price. Compared to other tiers, the quality is lower but this also holds for the price. The brand itself is not important for these consumers as their main focus is on price. In sum, we can classify the reasons for consumers to purchase the different brand tiers in the following way: For the lowest brand tier price serves as the main reason for purchase. The middle brand tier is purchased predominately for reasons such as value-for-money. Lastly, the high brand 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), we define loyalty 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 a focal 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.

We also explore the three-way interaction between MCSI, brand tier and loyalty tier. Not all customers who 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. Thus, we explore whether the effect of multichannel behavior significantly differs for brand-loyalty tier combinations (e.g., a customer in a lower loyalty tier buying a high-tier brand).

---- Insert Figure 1 about here ----

---- Insert Figure 2 about here ----

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

Main Effect of Multichannel Behavior on Purchase Outcomes

The most important issues identified by past research include how multichannel behavior affects customer spending (Kumar, Bezawada, and Trivedi 2018), and profitability (Kumar, Shah, and Venkatesan 2006) (also see Liu, Lobschat, and Verhoef 2018 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. 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 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 (Kushwaha and Shankar 2013; 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 leads to increased purchase frequency and accelerated purchases across multiple items and categories,

(2) the wide assortment of offerings across different channels offers multiple opportunities for consumers to purchase (from the firm) and increases 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 (Venkatesan, Kumar, and Ravishanker 2007).

So, prior research (e.g., Kumar et al. 2018; Montaguti, et al. 2016) strongly suggests that multichannel behavior should increase customer spending. Therefore, although we do not formally state it as an hypothesis, we expect to replicate prior studies by showing that multichannel behavior (i.e., high MCSI) has a positive effect on revenue per stay.

Moderating Effects on the Relationship of Multichannel Behavior and Purchase Outcomes

In addition, there are only a few studies 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. We extend this by considering brand tier as well as customer loyalty tier as moderators and study whether multichannel behavior remains valuable across different brand-loyalty tier combinations. We will explain our hypotheses on the effects of these moderators in the following.

Multichannel behavior and brand (tier). Prior research shows that brand and channel perceptions together determine purchase (intentions) (Dodds et al. 1991). As outlined above (also see figure 2), the different brand tiers appeal to different type of consumers in different purchase situations 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 that 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). The reasons multichannel behavior positively affects revenue outcomes, as outlined before, 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 customers to perceive less value in being a multichannel customer (i.e., using different sales channels) (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 this brand tier. For lower-tier brand customers, price is the most important attribute to assess the value of an offer and they focus less on service attributes, which might explain why these customers do not perceive additional value from multichannel behavior. Similar to high-tier brands customers, being a multichannel customer is not perceived as adding value for low-tier brand customers. Therefore, the positive effect of multichannel behavior on revenue is also expected to be lower for low-tier brand customers. However, this is expected to be different for middle-tier brands (i.e., volume tier), which are not solely purchased for their price, but also for their attributes – value-for-money. Middle-tier brand customers value both price and service cues, which creates opportunities for multichannel behavior to add value for these 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. Thus, we hypothesize the following:

Hypothesis 1: The positive effect of multichannel behavior on revenue per stay is smaller for high-tier and low-tier brands compared to middle-tier brands.

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 a customer's loyalty tier. Prior research 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 loyalty programs with more utility for customers residing in a higher tier. 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). Hence, 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 for this 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 Gollwitzet 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 effects[1] 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 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 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 2: The positive effect of multichannel behavior on revenue per stay will be weakened when customers reside in higher loyalty tiers.

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 service and/or price levels. We 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 program[2]. The final sample consists of 150,025 customers. In total, we have information on 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, 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. Next, we will provide more detailed information on our data.

Booking Channels

For each customer, we have information on which channel was used to book a stay with IHG for the observation period of 1 year (2016) (see appendix W1 for more information). Following prior research, we can 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 (individual) channel was used for each of the booked stays during the prior year(s) (i.e., the year before our observation period). This allows us to distinguish whether a customer uses the same (type of) channel or different channels to book their stays over time. Moreover, we can calculate the frequency of channel usage of each individual channel for each customer at the time of each purchase. With this information, we can also calculate the MultiChannel Share Index (MCSI), a measure for the intensity of multichannel usage. The development of this measure will be discussed in the model development chapter.

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 (intense) multichannel users.

Brand Tiers

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). In appendix W2 we contrast 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 more similar[3]. 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. Most bookings (across all brands) occur for loyalty tier 2 (and not loyalty tier 1 representing 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%).

Loyalty Tiers

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 (and 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.

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 apply for our model. Also, we investigate the extreme values of the variable. 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. For this purpose, we apply a method to delete +/- three standard deviations of the mean for log(revenue + 1) (e.g., Howell 1998; Iacobucci and Churchill 2010)[4]. This leaves us with 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, revenue per stay in the data is $197.13 ranging from $9 to $2157.

Model Development

In order to investigate the multichannel effectiveness across brands and loyalty tiers, we develop a (regression) model. 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.

MultiChannel Share Index (MCSI)

Our main interest is investigating 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 for each booked stay. We term this measure as the MultiChannel Share Index (MCSI). The equation of this measure can be found in equation 1.

$$(1)\ \text{MCSI}_{it} = 1 - \begin{pmatrix} \text{share web}_{it}^2 + \text{share app}_{it}^2 + \text{share htl}_{it}^2 + \text{share cro}_{it}^2 + \\ \text{share ota}_{it}^2 + \text{share gds}_{it}^2 + \text{share other}_{it}^2 \end{pmatrix}$$

Where share channel_{it} refers to the share of sales channel usage by a customer *i* at purchase time *t*, which translates into how often that specific sales channel was used by this customer out of the total number of times the customer used any IHG 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 0. In our data, the mean MCSI is 0.36 ranging from 0 to 0.84.

Besides the MCSI, we also conduct a robustness check with our model including the binary variable multichannel users (0: MCSI = 0 indicating single channel users, 1: MCSI ≥ 0.5 indicating multichannel users) and results are robust (also see robustness checks).

We provide an illustrative example of the calculation of our measure for 5 fictitious customers in table 2. 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. The illustration shows that the more sales channels used by the customer, the higher 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.

---- Insert Table 2 about here ----

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 a customer has booked before (= frequency) and the average spending across the previous purchases. All of these aspects are considered 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 during his/her past purchases[5]. Also, we have information on whether the customer redeemed points to purchase or used a free night voucher or bonus point package rate for his/her 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 his/her 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 distinguish between business and 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 on the weekend). Results are similar in sign and significance when replacing the proxy with this control (see robustness checks).

Self-Selection

Despite the findings from prior multichannel research which show that multichannel purchasing is 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; 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 volume. We control for this self-selection as various studies indicate that ignoring self-selection biases can lead to inaccurate estimation of the multichannel effects (e.g., Gensler, Leeflang, and Skiera 2012). For this purpose and in line with prior research (e.g., Montaguti, Neslin, and Valentini 2016), we employ propensity score matching to control for self-selection when studying multichannel behavior.

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 ≥ .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 model[6] (for more information see equation 2), in addition to estimating the model with the non-matched data.

Multichannel Model

In order to analyze the effectiveness of multichannel behavior, 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 as well as brand tier and customer loyalty tier – all for customer *i* at purchase occasion *t* – together with our control variables serve as independent variables, as shown in equation 2. Hence, taking into account all discussed aspects of the model development, the (full) model is specified as follows:

$$
\begin{aligned}
\log(\text{Revenue}_t) = {} & \alpha_{it} + \beta_1 \text{MCSI}_{it} + \beta_2 \text{Brand}_{it} + \beta_3 \text{LT}_{it} + \beta_4 \text{Brand}_{it} * \text{MCSI}_{it} \\
& + \beta_5 \text{LT}_{it} * \text{MCSI}_{it} + \beta_6 \text{Brand}_{it} * \text{LT}_{it} + \beta_7 \text{Brand}_{it} * \text{MCSI}_{it} * \text{LT}_{it} \\
& + \beta_8 \text{recency}_{it} + \beta_9 \text{frequency}_{it} + \beta_{10} \text{avgspending}_{it} + \beta_{11} \text{homeregion}_{it} \\
& + \beta_{12} \text{corporaterate}_{it} + \beta_{13} \text{dombrand}_{it} + \beta_{14} \text{voucher\_use}_{it} \\
& + \beta_{15} \text{redeemingpoints}_{it} + \beta_{16} \text{bpp\_use}_{it} + \beta_{17} \text{region}_{\text{key}_{it}} \\
& + \beta_{17} \text{domchannel}_{it} + e_{it}
\end{aligned}
\tag{2}
$$

In this model, we define the variables as follows:

$\log(\text{Revenue}_t)$	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 MultiChannel 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 W3). 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 proposed threshold (e.g., Leeflang et al. 2015). Therefore, we present the model results for all controls in the following.

Results

According to the model results, multichannel behavior generates higher revenues (compared to single channel behavior), but this is not always the case (see overview of results in table 3). Before discussing the results of our models, we present our model-free analyses.

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 .5 or higher, which is approximately 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 more intense multichannel users ($M_{single} = 205.52$, $M_{multi} = 204.77$, $p > .05$). However, we do find significant differences when comparing single vs. (more) intense multichannel users for the different brands. For brand tiers A and C, more intense multichannel users have a higher revenue per stay compared to single channel users (A: M_{single} = 188.65, M_{multi} = 191.32, $p < .001$; C: M_{single} = 246.44, M_{multi} = 262.23, $p < .001$). For brand tiers B and D, intense multichannel users have a lower revenue per stay compared to single channel users (B: M_{single} = 214.92, M_{multi} = 206.25, $p < .001$; D: M_{single} = 509.87, M_{multi} = 486.43, $p < .01$).

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

When looking at the difference between single and (more) 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 tier[6]. 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.

Model Results

Table 3 shows the parameter estimates of our multichannel model (equation 2) that are used to answer our research questions[7] (the results of the control variables can be found in appendix W4). The table includes the results of multiple models, which include all variables of our equation 2 step by step (see table 3 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 data[8].

In line with prior research, the main effect of MCSI 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 findings from prior research (e.g., Ansari, Mela, and Neslin 2008; Montaguti, Neslin, and Valentini 2016).

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), 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 H1 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 H2. 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. 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.

---- Insert Table 3 about here ----

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 W5). 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 the appendix W5. Across all robustness checks, we find support for our main results establishing confidence in our findings.

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, i.e., whether the effects are substantive and if they have managerial meaning other than merely being statistically significant (Verhoef, Kooge, and Walk 2016). We use the parameter estimates from model 3 and 4 in table 3 and translate these estimates 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 (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 customer with loyalty tier 4 purchasing brand tier C, and (6) a customer with loyalty tier 4 purchasing brand tier D.

For the effect of multichannel behavior, we consider multiple MCSI scores. 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 types 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 MCSI value, we calculate the (average) revenue per stay across the different brand tiers, customer loyalty tiers and brand-loyalty tier combinations of customers[9].

In table 4, we find higher average revenue per stay for higher MCSI scores across all brand tiers[10]. Similarly, higher average revenue per stay is found for higher MCSI scores across all loyalty tiers, except for the highest loyalty tier – tier 4. For this tier, we see that revenue per stay decreases when customers have higher MCSI. The highest revenue per stay is for a MCSI of 0, single channel customers.

We also find that higher MCSI lead to higher revenue per stay for most brand-loyalty tier combinations (see table 4). However, this is not the case for customers in loyalty tier 4 purchasing brand tiers C or D. For these combinations, 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.

---- Insert Table 4 about here ----

General Discussion

With the number of sales channels available to firms increasing (see e.g., MSI 2018-2020), firms can reach more consumers and provide consumers with additional convenience. However, the additional sales channels also increase complexity for firms' 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). In practice, firms also add more and more sales channels to their channel portfolios even though only one third of the marketing managers reports to feel confident in being able to deliver a promising multichannel strategy (CMO 2015). Hence, we provide a more precise understanding about multichannel effectiveness by assessing the moderating effects of brand tier and customer loyalty tier on the relation between multichannel behavior and purchase outcomes. 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), our results show that multichannel customers (vs. single channel customers) generate more revenue across all brands. However, this is not always the case. Opposing the general notion and prior literature, we show that 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.

Theoretical Implications

We contribute to existing literature in several ways. First, we extend prior research on the effects of customers' multichannel behavior (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). One exception is the study 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. Our results show that multichannel customers (vs. single channel customers) generate more revenue across all brands in line with prior research investigating the effect of multichannel customers on purchase behavior (e.g., Kumar, Bezawada, and Trivedi 2018). This finding is also in line with our hypothesis as the positive multichannel effect is smaller for the higher and lower-tier brands.

Second, we also extend prior research on the effects of multichannel behavior 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. Our results reveal that a *decreasing* intensity of multichannel usage by higher loyalty tier customers is associated with an *increase* in revenue. In other words, single channel customers generate more revenue for the highest loyalty tier.

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: $M_{\text{firm-owned}} = 219.63$, $M_{\text{partner-owned}} = 228.19$, $p = .41$). 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. We also investigated whether loyalty tier 4-customers use online or offline firm-owned channels across all brand tiers by conducting a simple regression (see appendix W4). 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.

Managerial Implications

Our results have important implications for firms (see table 5 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 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. We find that customers in highest loyalty tiers 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 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; 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. 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 is more pronounced when higher loyalty tier customers purchase a higher tier brand. High loyalty tier customers purchasing higher tier (upscale, luxury) brands should also be allowed to use their preferred single channel.

In sum, we suggest marketing managers 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.

---- Insert Table 5 about here ----

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 examine what specific channels work best in these cases. We made a first attempt to explore this, but future research 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. 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, 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. 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.

Conclusion

We study whether multichannel behavior is always more valuable by studying its effectiveness across brands and customer loyalty tiers. In contrast to conventional wisdom and prior literature, we show that multichannel customers are not always more valuable. Single channel customers generate more revenue for the highest-level loyalty tier and for the combinations of the highest-level loyalty tier and brand tiers. With these results, we strive to provide insights to firms that help them to getting a deeper understanding of the effectiveness of multichannel 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.

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Footnotes

[1] "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 et al. 2012, p. 987).

[2] The original data set included transactional data for about 4 years with information on customers who were sent (sales) promotions, and whether they redeemed these. Given our focus, we excluded customers who redeemed promotions. We focus on a one-year time period (2016) which has the least promotional activities.

[3] The standard deviation for MCSI is consistent across brand tiers, ranging from .21 to .24.

[4] By applying the method of deleting +/- three standard deviations of the mean, we delete 14% of the customers, which is equal to 18.5 % of the observations.

[5] We can determine the most frequent used channel (purchased brand) of each customer at each time based on the frequency of channel (brand) usage of each channel (brand) for each customer at the time of each purchase. In case of an even distribution, one of the most frequently used channels (purchased brands) is selected as the dominant option.

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

[7] 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).

[8] Model 5 in table 3 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.

[9] 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.

[10] 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.

Tables

Table 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

Table 2. Illustration of MultiChannel Share Index (MCSI)

	Customer A		**Customer B**		**Customer C**		**Customer D**		**Customer E**	
Channel	*Number of stays*	*share*^{2}	*Number of stays*	*share*^{2}	*Number of stays*	*share*^{2}	*Number of stays*	*share*^{2}	*Number of stays*	*share*^{2}
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	
Total number of stays	1		7		2		4		6	
MCSI (1 - $\Sigma(\text{share}^2)$)		0		.8571		.5		.75		.67

Table 3. 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	***
Main effects										
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	***
Interaction effects										
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*

Note: 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.

Table 4. scenario results across brand tiers, loyalty tiers, and their combinations

Scenario	MCSI = 0	MCSI = .33	MCSI = .5	MCSI = .84
Brand A	112.17	115.93	117.92	122.04
Brand B	119.10	123.10	125.21	129.59
Brand C	126.47	138.26	144.75	158.83
Brand D	225.88	238.91	245.92	260.72
Loyalty tier 1	112.17	115.93	117.92	122.04
Loyalty tier 2	120.30	123.11	124.59	127.62
Loyalty tier 3	137.00	138.82	139.77	141.71
Loyalty tier 4	159.17	157.09	156.02	153.89
Brand A Loyalty tier 1	112.17	115.93	117.92	122.04
Brand B Loyalty tier 2	126.47	129.85	130.32	135.30
Brand C Loyalty tier 3	156.02	167.22	173.30	186.27
Brand C Loyalty tier 4	192.48	189.33	187.73	184.53
Brand D Loyalty tier 3	230.44	235.05	237.46	242.41
Brand D Loyalty tier 4	284.29	283.35	282.87	281.90

Note: We use the estimates of models 3 and 4 (see table 3) 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 the revenue calculations of Brand A-D and Loyalty tier 1-4, and model 4 for the calculations of revenue for brand-loyalty tier combinations.

Table 5. Managerial table of results

<table>
<tr><th></th><th>Finding</th><th>Managerial implication</th></tr>
<tr><td>Main effect</td><td>Overall, multichannel customers (vs. single channel customers) generate more revenue</td><td rowspan="2">▪ Firms (with multiple brands) can invest in their channels in order to stimulate customers to use multiple sales channels.</td></tr>
<tr><td>Interaction multichannel and brand tier</td><td>Across all brand tiers, multichannel customers (vs. single channel customers) generate more revenue</td></tr>
<tr><td>Interaction multichannel and loyalty tier</td><td>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.</td><td>▪ 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.</td></tr>
<tr><td>Interaction multichannel, brand tier and loyalty tier</td><td>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.</td><td>▪ 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.</td></tr>
</table>

Figures

Figure 1. Conceptual framework

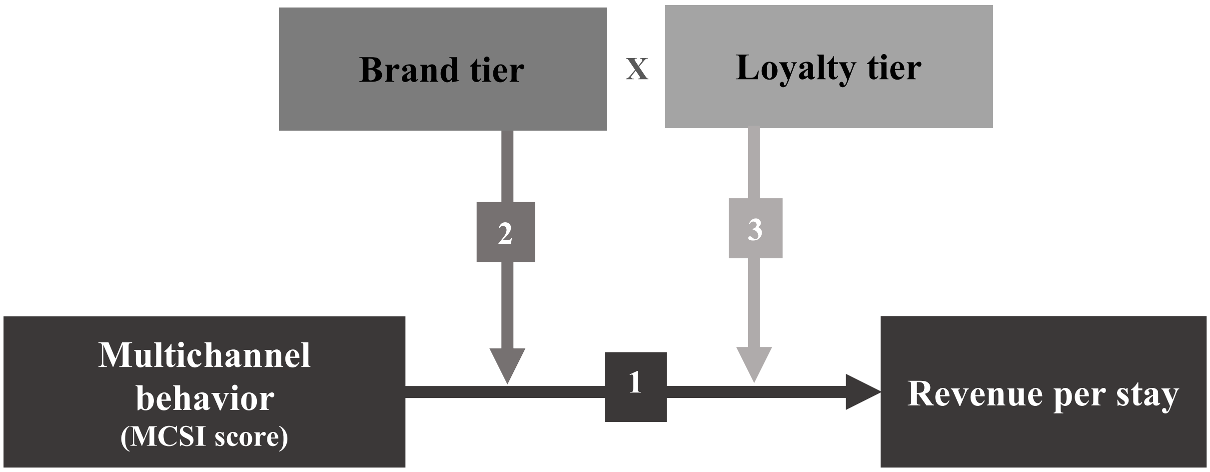
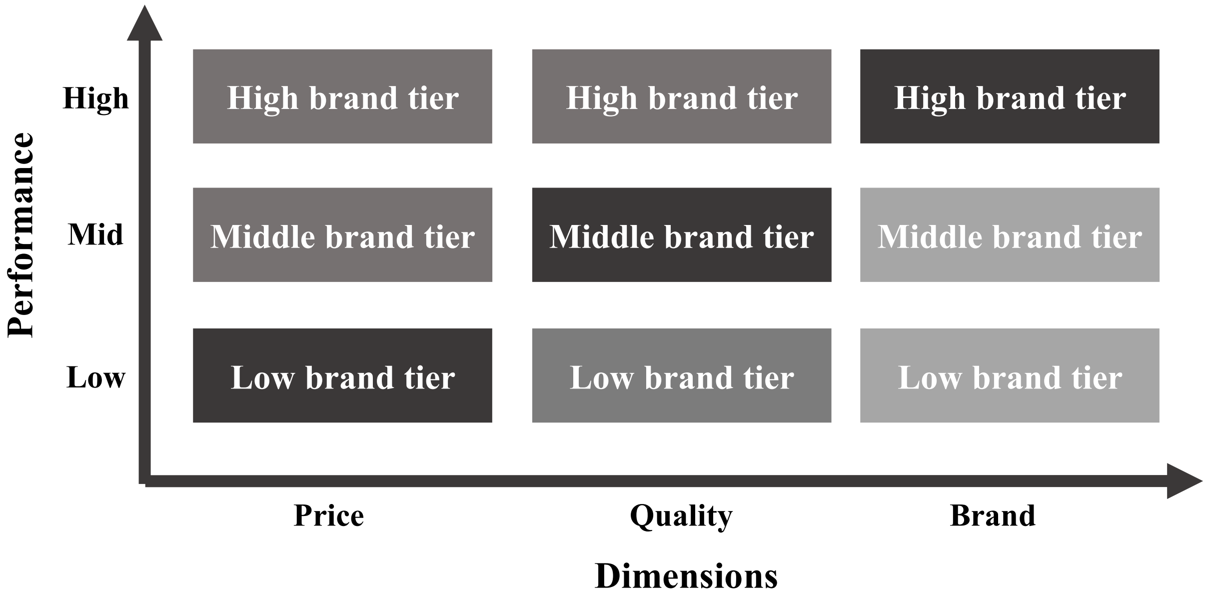


Figure 2. Positioning brand tiers along dimensions



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.

Web Appendix

Appendix W1: Sales channels

Table W1.1. 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. This is comprised mainly of corporate travel sites or travel-agent portals.	Offline	Partner-owned
Other	Other channels, which could mean not being identified. Not considered in our study.		

Appendix W2: Profile of brand tiers

Table W2.1. 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%)

Appendix W3: Descriptives and correlation table

Table W3.1: 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 W4: Results of the control variables and exploratory analysis

In addition to the expectations and effects from the conceptual framework, we can investigate some of the other estimates (see table 3 and W4.1). 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 table W4.1. For all models, the effect of recency and average spending is significant and (slightly) positive (β_8 = .00, p < .001; β_{10} = .00, p < .001), whereas the effect of frequency is significant and (slightly) negative (β_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 (β_{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 (β_{14} = -1.22, p < .001; β_{15} = -1.35, p < .001). The effect of customers using a bonus point package rate is positive (β_{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 W4.1: results control variables

	Model 1	Model 2		Model 3		Model 4		After PSM Model 5	
Controls									
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	***
Dom channel cro		0.00		0.00		0.00		0.00	
Dom channel gds		0.03	***	0.02	***	0.03	***	0.03	***
Dom channel htl		-0.03	***	-0.03	***	-0.03	***	-0.02	***
Dom channel ota		0.03		0.02		0.02		0.03	.
Dom channel oth		0.04	***	0.03	**	0.03	**	0.02	
Dom channel web		0.04	***	0.04	***	0.04	***	0.04	***

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

Table W4.2: 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 W5: Robustness checks

Table W5.1: 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*