New channel introduction and customer touchpoint experience in a multichannel environment

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Jing Li

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New Channel Introduction and Customer Touchpoint Experience in a Multichannel Environment

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CHAPTER 1

Introduction

Multi-touchpoint customer management becomes increasingly challenging for retailers given the proliferation of online shopping and the multiplicity of various channels and touchpoints. To address these challenges, this dissertation investigates (i) the role of customer heterogeneity and cross-channel competition on new online channel adoption and shopping behavior, (ii) the effects of instant customer experiences with multiple touchpoints on customer satisfaction and customer behavior. This chapter first explains the main focus of this dissertation, then presents the resulting research questions and research studies, and finally provides an overview of the following chapters in this dissertation.

1.1. Introduction

Today customers interact with firms for browsing, purchasing products and services, and obtaining after-sales services through multiple channels and touchpoints namely: stores, catalogs, the web, telephones, kiosks, mobile devices, social networks etc. There are at least two prominent phenomena in the multi-touchpoint environment. First, the Internet has become one of the mainstream sales channels, which fundamentally changes customers' shopping behavior. The online retail sales in U.S. occupied 9% of the $3.2 trillion total retail market in 2013 and will continue to grow at an annual growth rate of nearly 10% through 2018 (Forrester Research 2014c). In addition to purchase directly through the Internet, customers increasingly use the online channel to gather information before purchasing in stores or other channels, such that the web influenced 59% of U.S. total retail sales in 2013.

Second, new touchpoints, such as mobile devices and social media, play an increasingly pivotal role on customer decision-making. Although the sales on tablet, smartphones or social network has so far represented a small fragment of the total sales, many customers use these channels to serve their shopping purposes: over 69% of smartphone or tablet users will use these devices to browse products, search store location or check prices, and 45% customers will use social media to assist in their shopping decisions (Deloitte 2014). In spite of the great opportunities from multichannel shopping, the study of Forrester Research (2014a) shows that nearly all (94%) surveyed retailers reported significant barriers to managing and integrating multiple channels or touchpoints effectively. This proliferation of channels and touchpoints thus provide great opportunities for academics to produce insights that can help address these challenges (Van Bruggen et al. 2010; Neslin and Shankar 2009).

In the multichannel literature, a channel is defined as a contact point through which the firm and the customer interact (Neslin et al., 2006, Grewal et al., 2009). The multichannel customer management refers to "*the design,* *deployment, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development.*"(Neslin et al. 2006, p.96). With the prolification of new channels and touchpoints, resent research suggest considering all direct and indirect touchpoints during customer shopping journey (Baxendale, Macdonald, and Wilson 2015; Lemke, Clark, and Wilson 2011; Meyer and Schwager 2007). Following Wilson et al. (2013, p.1), a touchpoint refers to "*an encounter type*", and an encounter is "*a single episode of direct or indirect contact with the brand*". The touchpoint such can be a marketing channel through which customers interact with firms for shopping (Neslin et al. 2006), as well as the one-way communication (e.g., mass, direct and in-store communications) exerted by firms, or word-of-mouth (WOM) and publicity in which neither the firm nor its channel partners are directly involved (Baxendale et al. 2015; Wilson et al. 2013). This dissertation focuses on two research issues of the multichannel and multi-touchpoint customer management: (1) new channel introduction in a multi-channel environment and (2) customer experience with multiple touchpoints.

1.1.1. Multichannel Customer Management

Existing literature in the multichannel customer management focuses on the issues like channel choice (Chintagunta, Chu, and Cebollada 2012; Kumar and Venkatesan 2005; Valentini, Montaguti, and Neslin 2011), channel migration (Ansari, Mela, and Neslin 2008; Konx 2006; Thomas and Sullivan 2005; Venkatesan, Kumar, and Ravishanker 2007), multichannel customer segmentation (Konuş, Verhoef, and Neslin 2008; Kushwaha and Shankar 2013; Thomas and Sullivan 2005), the allocation of marketing efforts across channels (Kushwaha and Shankar 2008; Wiesel, Pauwels, and Arts 2011), multichannel behavior in the multiple shopping phases (Frambach, Roest, and Krishnan 2007; Gensler, Verhoef, and Böhm 2012; Verhoef, Neslin, and Vroomen 2007), and the value of multichannel versus single channel customers (Ansari et al. 2008;

Kushwaha and Shankar 2013). A number of studies also investigate the impact of new channel introduction and multichannel strategy on total sales or other firm performances (Gensler, Leeflang, and Skiera 2012; Lee and Grewal 2004; Pauwels and Neslin 2015; Wolk and Skiera 2009), the performances of other channels (Avery et al. 2012; Biyalogorsky, Eyal and Naik 2003; Moe and Yang 2009; Pauwels et al. 2011), customer loyalty (Gensler, Dekimpe, and Skiera 2007; Wallace, Giese, and Johnson 2004), and customer retention (Boehm 2008; Campbell and Frei 2009; Xue, Hitt, and Chen 2011).

Previous research has made significant progress in clarifying the above issues in the area of multichannel customer management; however, several research and managerial questions still remain and thus need further investigation (Neslin and Shankar 2009). For example, it is still unclear how customers' response to a new online channel introduction and whether the effect of online channel adoption on customer purchase volume vary across different segments. Understanding customer heterogeneity in this matter helps firm set up their multichannel segmentation scheme which is a key issue in designing effective multichannel strategies (Neslin et al. 2006). Another nearly untapped issue is the effect of competition on a firm's multichannel strategy (Neslin and Shankar 2009). For instance, how do competitors' online and offline channels affect customer channel choice? Specifically speaking, do customer perceive the same channel differently from one firm to another? Therefore, the *first* objective of this research is to obtain a deeper understanding of customer multichannel behavior with respect to the effects of customer heterogeneity and cross-channel competition on new channel adoption and multichannel shopping behavior.

1.1.2. Customer Experience in a Multi-Touchpoint Environment

The emergence and proliferation of new touchpoints (online, mobile, social media) raise the challenges to create superior customer experience – one of the central objective in today's retailing environment (Verhoef et al. 2009). Customer experience refers to "*the internal and subjective response customers have to any direct or indirect contact with a company*" (Meyer and Schwager 2007, p. 118). In a similar vein, Verhoef et al. (2009) on p. 32 emphasize the holistic nature of customer experience that "*encompasses the total experience, including the search, purchase, consumption, and after-sale phases of the experience, and may involve multiple retail channels*". Therefore, a customer's experience derives not only from two-way interactions between firms and customers such as marketing channels, but also from one-way communications exerted by firms such as mass advertisements, as well as indirect contacts such as publicity and word-of-mouth. However, most marketing literature covers the experiences with limited types of above touchpoints (i.e., Ahluwalia et al. 2000; Chevalier and Mayzlin 2006; Onishi and Manchanda 2012; Trusov et al. 2009). Therefore, the *second* objective of this thesis is to gain a better understanding of the holistic customer experience deriving from multiple touchpoints that covers all direct and indirect contacts with the brand, focusing particularly on the consequences of customer multi-touchpoint experiences.

To achieve above objectives, the dissertation: (i) compares customer purchase amount and investigates the effects of new online channel adoption on purchase volumes across different segments; (ii) investigates the effects of cross-channel competition on channel migration and firm purchase volume; (iii) explores the influence of instant and holistic customer experience with multiple touchpoints on customer satisfaction and behavior. In the following sections, I will first discuss the research questions, then introduce the research studies, and finally outline the structure of the dissertation.

1.2. Research Questions

1.2.1. Purchase Amount and the Effects of New Online Channel Adoption on Purchase Volumes Across Segments

Innovation diffusion research suggests that earlier adopters of a product or service are more valuable, because they are heavier shoppers or more frequent users (Goldsmith and Flynn 1992; Mahajan, Muller, and Srivastava 1990; Prins and Verhoef 2007), and more influential than late adopters (Mahajan, Muller, and Wind 2000). However, it is still unclear whether the earlier adopters of a new online channel are critical to the success of new online channel introduction, especially with respect to the revenue generated. This dissertation thus formulates the following research question:

RQ$_{1a}$: *Do earlier adopters of a retailer's online channel purchase more than other customer segments adopting the online channel?*

To investigate customer purchases across segments, it is also important to clarify the changes of purchase volumes due to online channel adoption. Although a vast number of studies investigate the effects of online channel adoption on customer shopping behavior (Ansari et al. 2008; Biyalogorsky, Eyal and Naik 2003; Campbell and Frei 2009; Gensler, Leeflang, et al. 2012), far less studies examine its effects on customer behavior across segments (Pauwels et al. 2011), especially the influence of online *transactional* channels. Moreover, previous research suggests that customers alter their behaviors after online channel adoption due to the influence of intrinsic benefits of online shopping and marketing communications (Ansari et al. 2008; Ariely 2000; Montoya-Weiss, Voss, and Grewal 2003; Neslin et al. 2006), but having not yet confirmed which one is the more dominant factor. The lack of research results in the following research question:

RQ$_{1b}$: *How does customer adoption of the retailer's online transactional channels affect purchase volumes of different customer segments who adopt the online channel at different times?*

1.2.2. *The Effects of Cross-Channel Competition on Channel Migration and Firm Purchase Volume*

Although the Internet has become a mainstream sales channel, plenty of offline retailers have not yet adopted or even made plans to introduce the online sales channel. Prior to a late entrant introducing its own online channel, customers might have already had similar online shopping experience from the competitors' online channels. Existing literature indicate that prior channel usage greatly affects subsequent channel choice (Ansari et al. 2008; Inman, Shankar, and Ferraro 2004; Montoya-Weiss et al. 2003), and customer shopping behavior depends on competitors' marketing actions (Van Diepen, Donkers, and Franses 2009; Moe and Yang 2009; Prins and Verhoef 2007). However, it is unclear how customers' previous purchases from competitors' online and offline channels affect their channel choices and adoption of a new online channel. Furthermore, previous studies suggest that a firm's existing customers and the new customers acquired after the new online introduction may respond differently to marketing efforts and new channel introduction (Avery et al. 2012; Valentini et al. 2011). Yet, it is still unknown whether the cross-channel competition affects channel migration of the two groups differently. In response, this dissertation raises the following research question:

RQ$_{2a}$: *How do customers' previous purchases from competitors' online and offline channels affect channel migration of existing and new customers?*

The increasing competitiveness of multichannel environments also makes it vital to investigate the consequences of new channel introductions, especially its effects on competition among firms. A number of studies suggest that firms benefit from introducing online channels, through increased sales and customer loyalty or retention (Boehm 2008; Campbell and Frei 2009; Coelho, Easingwood, and Coelho 2003; Wallace et al. 2004), whereas other studies reveal negative effects of online channel adoption on purchase volumes (Ansari et al. 2008; Thomas and Sullivan 2005). In this debate, there is no indication of how customers' adoption of a new online channel affect their purchases with competitors. Yet a clear understanding of the effects of competition in multichannel marketing should provide a more accurate assessment of the value of adding a new channel to a retail assortment (Dholakia et al. 2010; Moe and Yang 2009; Neslin and Shankar 2009). The lack of research raises the following research question:

RQ$_{2b}$: *How do customers' adoption and use of a new online channel affect their purchases with competitors and the focal firm?*

1.2.3. The Effects of Instant Multi-Touchpoint Customer Experience on Customer Satisfaction and Behavior

Early studies determine customer satisfaction as a function of expectation, perceived quality, and disconfirmation (Anderson and Sullivan 1993; Boehm 2008; Oliver 1980). Recent studies suggest that satisfaction might be shaped by holistic experiences derived from all touchpoints between customers and brands (Lemke et al. 2011; Meyer and Schwager 2007; Verhoef et al. 2009). Extensive research in the multichannel domain investigates the effects of different types of touchpoints on customer behavior and firm performance, while most studies consider the effects of a few touchpoints on customer shopping behavior (i.e., Ahluwalia et al. 2000; Assmus, Farley, and Lehmann 1984; Chevalier and Mayzlin 2006).

It is important to capture the entire multi-touchpoint experience in one research framework, as every encounter between brands and customers could influence customers' overall brand experiences and affect their behaviors (Gentile, Spiller, and Noci 2007; Meyer and Schwager 2007; Verhoef et al. 2009).

However, no studies trace a customer's real-time and holistic experiences with multiple touchpoints during the shopping journey, and investigate the effects of the instant multi-touchpoint experience on customer satisfaction and behavior. This raises the following research questions:

RQ$_{3a}$: *How do holistic customer experiences with multiple touchpoints affect customer satisfaction?*

RQ$_{3b}$: *How do the instant multi-touchpoint experiences affect online and offline behavior (i.e. transactions) over time?*

Furthermore, it is unclear how the volume and valence of various touchpoints affect customer satisfaction and behavior. The volume attribute reflects the frequency or amount of a touchpoint's encounters, and the valence attribute captures the instant emotion (i.e., positivity and negativity of user ratings) stimulated by the experience through an encounter (Duan, Gu, and Whinston 2008; Liu 2006). Most studies focus on the effect of touchpoint volume (Assmus et al. 1984; Deighton, Henderson, and Neslin 1994; Dijkstra, Buijtels, and van Raaij 2005; Trusov et al. 2009). For those that consider the valence effect, they mostly investigate the influence of earned media (i.e., WOM or publicity) (Ahluwalia et al. 2000; Liu 2006; Tirunillai and Tellis 2012). No studies capture the valence effect of the touchpoints in additional to the earned media, resulting in the following research question:

RQ$_{3c}$: *To what extent do the volume and valence attributes of touchpoint experiences differ with respect to their effects on customer satisfaction and behavior?*

1.3. Research Studies

1.3.1. Study 1: The Hare and the Tortoise: Do Earlier Online Channel Adopters Purchase More?

The objective of study 1 is to compare customer purchase amount and investigate customers' varying response to new online channel adoption. To answer RQ_{1a} and RQ_{1b}, study 1 segments customer into different groups on the basis of channel adoption duration and purchase amount before adoption, and examines the effects of online channel adoption on purchase volumes across segments over time. This research contributes substantial knowledge on identifying heavy shopper segments and knowing their behaviors. This study also contributes to the theory of multichannel customer shopping by providing empirical evidence in support of the predominant influence of intrinsic benefits on customer behavior after the online channel adoption.

To achieve the research objective, study 1 uses daily transactional data from a multichannel French retailer that sells healthy and natural products. The data cover 12.5-year purchase history of 3,270 customers. This study employs a series of models, including (1) a latent class cluster analysis (LCCA) to segment customers on the basis of their online adoption duration and purchase amount before adoption, (2) a propensity score matching (PSM) technique to control for the effect of self-selection, and (3) a Type II Tobit model and difference-in-difference (DID) analysis to investigate the impact of online channel adoption on purchase volumes of different segments.

1.3.2. Study 2: Customer Channel Migration in the Competitive Environment: the Effects of Cross-Channel Competition

Study 2 aims to understand customer channel migration in a competitive and multichannel environment. To answer RQ_{2a} and RQ_{2b}, study 2 specifically investigates the effects of customer previous purchases from competitors' online and offline channels on the channel migration of a firm's new and existing customers, and the effects of online channel adoption and use on purchase volumes of competitors and of the focal firm that introduces the new online channel. This study is the first to integrate individual transaction data from competing firms and uncover the effects of competitors' channels on multichannel customer shopping behavior. Findings of this study provide valuable insights on introducing new channels and managing multiple channels in the competitive environment.

To achieve the research objective, study 2 uses a unique individual transaction data gathered from ten French multichannel retailers competing in the same category (home décor). Each customer has a unique identity that is identical across all retailers and is used to track customer multichannel purchases from these firms over time. The data cover purchase history of 20,570 customers, spanning 42 months before and 54 months after a focal firm introduced a new online channel. This study employs multivariate probit model with sample selection and Type II Tobit model.

1.3.3. Study 3: How Do Instant Multi-Touchpoint Experiences Affect Customer Satisfaction and Behavior? A Real-Time Experience Tracking Approach

The aim of study 3 is to explore holistic customer experiences with multiple touchpoints during their shopping journeys. To answer $RQ_{3a\text{-}c}$ study 3 specifically investigates the effects of instant and holistic multi-touchpoint experiences on customer satisfaction and behavior, and differentiates between a touchpoint's valence and volume effect. The study is the first to link customers' instant and multi-touchpoint experiences to their satisfaction and behaviors, and introduces a novel, real-time experience tracking approach. This research provides in-depth insights on creating superior customer experiences and managing these experiences across various touchpoints.

To achieve the research objective, study 3 conducts a novel and mobile-based real-time experience tracking approach to collect timely and holistic customer experiences with multiple touchpoints. Each participating customer sends a structured text message whenever he or she encounters the focal brand, and the messages contain the type of touchpoint, the encountered brand, and the valence of the encounter that the customer experiences (Baines et al. 2011; Wilson et al. 2013). Participants are also required to fill in pre-study and post-study online surveys and a daily online diary. With this method, customer touchpoint experience data is collected from three categories (supermarket, banking, and healthcare) over a four-week period. The initial data set consists of 448 customers reporting more than 8,000 encounters from the following touchpoints in three categories (i.e., supermarkets, banking and healthcare): the television, newspaper, billboard, direct communication, online banner, in-store communication, publicity, offline WOM, and online and offline transaction. This study employs dynamic univariate/bivariate probit, linear regression, and Principle component analysis to test models.

1.4. Outline

Table 1.1 outlines the main research characteristics of the three studies. The reminder of this dissertation is organized as follows. Chapter 2 present study 1 that compares customer purchase amount and investigates the effects of new online channel adoption on purchase volumes in different segments who adopt the online channel at different times. Chapter 3 contains study 2 that explores the impacts of cross-channel competition on channel migration and firm purchase volumes. Chapter 4 presents study 3 that investigates the effects of instant multi-touchpoint experiences on customer satisfaction and behavior. Finally, chapter 5 summarizes main findings, discusses their implications and research limitations, and offers suggestions for further research.

Table 1.1: Outline of Main Research Characteristics

	Study 1 (Chapter 2)	**Study 2 (Chapter 3)**	**Study 3 (Chapter 4)**
Subject	Customer purchase amount and effects of new online channel adoption on purchase volumes across segments	Effects of cross-channel competition on channel migration and firm purchase volume	Effects of instant multi-touchpoint experiences on customer satisfaction and behavior
Data	Longitudinal transactional data	Longitudinal transactional data	Longitudinal survey data
Initial sample size	3,270	20,570	448
Method	• Latent class analysis • Propensity score matching • Difference-in-difference analysis • Type II Tobit model	• Multivariate probit model with sample selection • Type II Tobit model	• Dynamic bivariate/univariate probit model • linear regression • Principle component analysis

CHAPTER 2

The Hare and the Tortoise: Do Earlier Online Channel Adopters Purchase More? [1]

Earlier adopters of a product or service tend to be more valuable than later adopters. Does this empirical generalization equally apply to earlier adopters of a multichannel retailer's new online channel too? This study segments customers on the basis of their responses to a new online channel and investigates the effects of their online channel adoption on purchase volumes across segments. The data cover 12.5 years of purchase history and individual transactions at a large French retailer of natural healthy products. Contrary to the conventional wisdom, it is not innovators or early adopters but rather the late majority segment that purchases more than the other segments, both before and after online adoption. Adoption of the firm's new online channel does not influence purchase volumes of heavy shopper segments (late majority and innovators), whereas light shopper segments tend to increase their purchases after adopting this new channel.

---

[1] This chapter has been published in the *Journal of Retailing* – Special Issue on Multi-channel Retailing and Customer Touch Points as: Li, J., Konuş, U., Pauwels, K. and Langerak, F.: The Hare and the Tortoise: Do Earlier Online Channel Adopters Purchase More?. 91 (2), 289–308.
Early versions of this study have been presented at the 2014 Informs Marketing Science Conference (Atlanta, U.S.) and 2013 Informs Marketing Science Conference (Istanbul, Turkey).

2.1. Introduction

Are earlier adopters key to marketing success? When it comes to the adoption of new products and services, research shows that earlier adopters purchase and use products more often and are greatly influenced by media promotions (Goldsmith and Flynn 1992; Mahajan, Muller, and Srivastava 1990). They also may be more profitable than late adopters, because firms often charge a premium price in the early phases of a product's life cycle. Furthermore, earlier adopters have critical influences on uptake decisions by later adopters, because they spread the attitudes or satisfaction they develop toward the innovation (Mahajan et al. 2000). In considering both financial and social effects, Hogan, Lemon and Libai, (2003) emphasize that the loss of an earlier adopter costs a firm much more than the loss of a later adopter. By targeting earlier adopters, firms can ensure faster returns on their investments and take advantage of social spillover effects for diffusing new products.

However, are earlier adopters also critical to the success of a newly introduced marketing channel? Driven by the Internet and mobile technology, retailers increasingly introduce new online channels to supplement existing channels, retain existing customers, and acquire new customers. Existing offline customers adopt the retailer's new online channel at different time periods and purchase through multiple channels; the resulting multichannel shoppers spend more than single-channel shoppers (Ansari et al. 2008; Neslin et al. 2006; Thomas and Sullivan 2005). Some studies suggest that customers who are faster to adopt a new (online) channel exhibit greater purchase frequency and transaction volume before the adoption (Venkatesan et al. 2007; Xue et al. 2011); no study has investigated the different behaviors or features of customer groups that adopt a retailer's new channel earlier or later than other customers though. For example, do innovators or early adopters of new online channels purchase more than the majority segments or laggards? Can we distinguish among segments that adopt new channels at different periods? Identifying the most valuable customer groups and understanding their characteristics could help retailers allocate their limited marketing resources more effectively across customer segments thus improve their overall profits. Effective market segmentation is critical to firm profitability and survival (Blattberg, Kim, and Neslin 2008; Bolton and Myers 2003; Viswanathan et al. 2007), so we investigate the monetary contributions and characteristics of different customer segments, identified on the basis of their adoption duration of newly introduced online channels and their purchase amounts prior to that adoption.

To investigate customer purchases across segments, we also clarify the extent to which customers change their purchase volumes due to online channel adoption. Plenty of studies investigate the effects of online channel adoption or use on customer shopping behaviors over time (Ansari et al. 2008; Biyalogorsky, Eyal and Naik 2003; Campbell and Frei 2009; Gensler, Leeflang, et al. 2012). Far less research explores its effects on customer behavior across different segments, with the notable exception of Pauwels et al. (2011), who investigate the influence of an informational website. We seek to extend this literature stream by empirically investigating the effects of an online transactional channel on purchases by various segments that adopt the channel at different times. If the effects vary across segments, firms should differentiate their multichannel strategies accordingly. Thus we investigate two key research questions:

(1) *Do earlier adopters of a retailer's online channel purchase more than other adopter segments, identified on the basis of their adoption duration of newly introduced online channels and purchase amounts prior to the online adoption?*

(2) *How does customer adoption of the retailer's online transactional channels affect purchase volumes of different customer segments, identified by adoption duration?*

We rely on latent class cluster analysis (LCCA) to segment customers according to their online adoption duration and purchase amounts before adoption, then profile the identified segments using various covariates related to their demographics and shopping behaviors after adoption (Vermunt and Magidson 2005). To estimate the impact of online channel adoption on customer behavior, we control for the potential effect of customer self-selection (Boehm 2008; Campbell and Frei 2009). Thus in the second step, we employ a propensity score matching (PSM) technique to determine a matched offline customer group for each online adopter segment (Dehejia 2005; Rosenbaum and Rubin 1985). Finally, for each segment, we apply a Type II Tobit model to investigate the impact of online channel adoption on monthly purchase incidence and monetary value per transaction (order size) over time (Ansari et al. 2008). To supplement this model, we undertake a difference-in-difference analysis (DID) to examine changes in purchase volume and frequency, one year after the adoption of the online channel (Campbell and Frei 2009).

With these approaches, our research reveals that the heaviest shoppers are neither innovators nor early adopters of a new online channel but rather the customers in the late majority segment. Most research on customers' adoption of new products or services focuses on the contributions of earlier adopter segments; our study reveals that later adopters (late majority) can be the most valuable customer group, both before and after the online channel adoption. In addition, we demonstrate the effects of online channel adoption on purchase volumes across different segments, which can help firms predict the consequences of their online channel introduction more precisely and identify key challenges for different customer segments. Considering that our results show that purchases by heavy shopper segments (i.e., late majority and innovator) are unaffected by their adoption of online channels, whereas customers in other segments (i.e., early adopter, early majority, and laggard) tend to increase their purchase volumes after adopting, retailers should consider developing different strategies to address segment-specific challenges.

In the next section, we propose and detail a two-step conceptual framework that covers customer segmentation and the behavioral consequences of online adoption. After we describe the data and variable operationalization, we present a series of analyses, and then the results. Finally, we summarize our key findings and discuss their managerial implications, limitations, and further research options.

2.2. Conceptual Development

The two-part conceptual framework of this study in Figure 2.1 features (1) customer segmentation on the basis of customer heterogeneity (left side) and (2) the effects of online channel adoption on purchase volumes across different segments (right side).

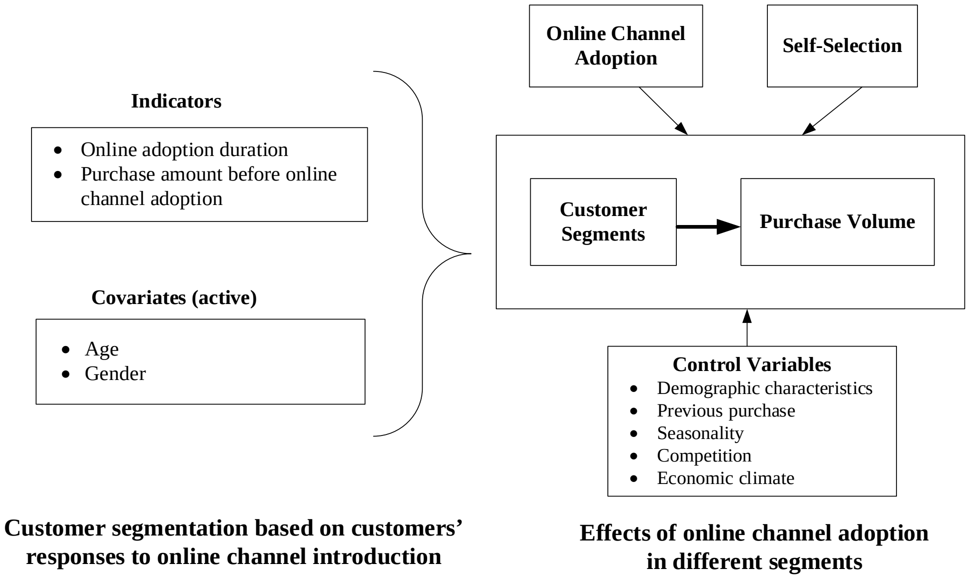

Figure 2.1: Conceptual Framework of Online Channel Adoption

2.2.1. Identifying Customer Segments

Increasing variety of marketing channels allows customers to adopt new channels and become multichannel shoppers. For retailers, multichannel customer segmentation, which segments customers according to their shopping behaviors across multiple channels, offers an effective method for designing multichannel marketing strategies (Neslin et al. 2006). The underlying logic is that customers self-select into channels that invoke different costs, related to time, travel, shopping, and so forth (Anderson, Day, and Rangan 1997); in addition, psychological and economic attitudes, together with expected benefits and costs, affect channel preferences and uses (Konuş et al. 2008). For example, Thomas and Sullivan (2005) identify two customer segments—multichannel shoppers and store-only shoppers—and cite the impacts of price, product category, distance, marketing spending, and previous purchases on channel choices. Konuş et al. (2008) segment customers by channel choices across multiple phases (e.g., information search, purchase) of the shopping process. Different from previous studies, we identify customer segments based on two indicators: adoption duration and purchase amount before online channel adoption.

Adoption duration. Customers adopt product and service innovations at different times after launch (Mahajan, Muller, and Srivastava 1990; Rogers 2003). Depending on how quickly the adoption takes place, Rogers (2003) classifies innovation adopters into five groups: innovator, early adopter, early majority, late majority, and laggard. These segments differ in their demographics, psychographics, social class, and life styles (Gatignon and Robertson 1985; Rogers 2003). For example, early adopters tend to have higher income and status occupations, more education, a socially forward attitude, and more experience with other technical products (Mahajan, Muller, and Srivastava 1990; Rogers 2003). Innovators tend to be risk-taking, impulsive, dominant, inner-directed, flexible, and venturesome (Foxall and Goldsmith 1988; Goldsmith and Flynn 1992). Groups that adopt innovations at different times might have distinct shopping and behavioral patterns too, such that earlier adopters use new products more frequently but only for their basic functions (Goldsmith and Flynn 1992; Huh and Kim 2008; Mahajan, Muller, and Srivastava 1990; Prins and Verhoef 2007). Similarly, earlier adopters of new e-services exhibit higher service usage levels than late adopters (Prins and Verhoef 2007).

Purchases before online channel adoption. We are primarily interested in comparing segments' purchases that are represented by the purchase amounts—monetary contributions by customers (Campbell and Frei 2009; Gensler, Leeflang, et al. 2012). More interactions with a firm might enhance customer trust more quickly (Morgan and Hunt 1994) and shorten the time before the customer adopts the firm's new channels. Customer expenditures also contribute to behavioral loyalty, which accelerates customer adoption speed (Demoulin and Zidda 2009). Empirical evidence shows that customers who adopt transactional channels faster also exhibit greater transactional frequency before their adoption (Venkatesan et al. 2007; Xue et al. 2011). Therefore, we posit:

H_1: *Segments with higher prior purchase amounts adopt new (online) channels faster.*

One of the crucial aspects of the segmentation framework is to explore the impact of covariates on the membership of segmentation and to profile features of identified segments according to these covariates.

Covariates. We include customer demographics, such as age and gender, in our framework as covariates that can affect the segmentation membership. Such demographic variables influence online channel adoption (Campbell and Frei 2009; Xue et al. 2011), channel adoption duration (Venkatesan et al. 2007), and channel choice (Ansari et al. 2008; Inman et al. 2004; Konuş et al. 2008). For example, Venkatesan et al., (2007) find that male customers are more likely to adopt additional channels faster, but their income levels do not affect channel adoption. Xue et al. (2011) identify a curvilinear relationship between age and online channel adoption speed: Younger customers likely exhibit quicker adoption. Because the effects of demographic controls on behaviors often are insignificant or inconsistent (Konuş et al. 2008), we do not formulate a formal hypothesis but rather include age and gender as covariate variables.

Moving from predicting channel adoption to predicting its consequences, we next discuss whether and how online channel adoption impacts customer spending for different adopter segments.

2.2.2. Effects of Online Channel Adoption on Purchase Volumes of Different Customer Segments

Extensive multichannel management studies investigate the effects of online channel adoption and usage on customer behavior and firm performances over time. Some studies employ aggregated, firm-level data; for example, Geyskens, Gielens and Dekimpe (2002) determine that adding an Internet channel accelerates stock market returns, and Lee and Grewal (2004) find similar results in the compact disc category. Another research stream focuses on disaggregated data, related to individual customer panels. Campbell and Frei (2009) reveal that customer adoption of online banking is associated with a substantial increase in total transaction volume, and Gensler et al. (2012) show that the use of online channels increases customer revenue. Furthermore, Boehm (2008) indicates a strong positive impact of online channel use on customer retention. Although most studies suggest that online channel adoption and use promote customer demand, Ansari et al. (2008) find that online usage is negatively associated with long-term purchase frequency.

Despite rich research on the consequences of online channel additions, few studies investigate the effects of online channel adoption by considering the impact of different customer segments (i.e., Pauwels et al., 2011). As is well established in marketing, customer heterogeneity critically affects customer responses to a firm's multichannel strategies (Kushwaha and Shankar 2013; Thomas and Sullivan 2005). Therefore, we expect that the effects of online transaction channel adoption on customer purchases might vary across customer segments that differ in their purchase volumes prior to online channel adoption. To formulate our hypotheses, we clarify precisely why we expect customers to alter their shopping behaviors in response to online channel introduction, according to two opposing mechanisms: intrinsic benefits and marketing communications.

Intrinsic benefits. Customers change their behaviors after online channel adoption, because of the benefits they perceive from online shopping. The online shopping makes it easier for customers to search for information and compare products (Ariely 2000). Therefore, customers perceive greater information control than they would if they relied solely on offline channels (Gensler, Leeflang, et al. 2012). Greater information control likely leads to higher customer satisfaction and higher repurchase rates (Meuter et al. 2000; Mittal and Kamakura 2001). Moreover, online channels offer customers greater convenience and accessibility, through constant availability and interactivity, the convenience of buying from home, and enhanced access to personalized offers (Brynjolfsson, Hu, and Smith 2003; Gensler, Leeflang, et al. 2012; Montoya-Weiss et al. 2003; Wolk and Skiera 2009). Finally, shopping online could reduce transaction costs, including the costs of search, travel, time, and physics (Chircu and Mahajan 2006; Varadarajan and Yadav 2002), though these costs also depend on customer heterogeneity (Chintagunta et al. 2012). Because of these benefits, customer' overall purchase volumes from online and offline channels likely increase after they adopt a firm's online channel (Campbell and Frei 2009; Xue et al. 2011).

Segments of heavy shoppers may perceive fewer benefits of online shopping than light shopper segments though. Customers' perceptions of the usefulness and use of innovative technology (e.g., Internet channel) depend on their preference for the status quo (Falk et al. 2007; Limayem, Hirt, and Cheung

2007). And the habitual behavior forms through multiple repetitions of decisions (Aarts, Verplanken, and Knippenberg 1998; Orbell et al. 2001). Because frequent interactions with offline channels cultivate offline shopping habits, heavy shoppers likely induce a stronger preference for these channels than is the case for lighter shoppers. Falk et al. (2007) note that satisfaction with offline channels reduces the perceived usefulness and enhances the perceived risk of online shopping, and Montoya-Weiss et al. (2003) show that positive perceptions of service quality in an existing channel can inhibit uses of a new online channel. Moreover, according to Konuş, Neslin and Verhoef (2014), customers who prefer a focal firm are less affected by changes to its channel repertory (e.g., elimination of a catalog channel), possibly because heavy shoppers, who are more familiar with the firm's offerings, perceive fewer changes to their shopping benefits (e.g., search convenience, shopping enjoyment). Integrating these findings, we predict that heavy shoppers likely perceive online shopping as less useful and beneficial than light shoppers. If customer behavior mainly reflects the intrinsic benefits of online shopping, we expect:

H_2: *Online firm channel adoption has more positive effects on the purchase volumes of light shopper segments than on those of heavy shopper segments.*

Marketing communications. Customers alter their purchase volumes after adopting online channels, likely because they receive more marketing contacts through varied channels (Kumar and Venkatesan 2005; Neslin et al. 2006). Ansari et al. (2008) note that multichannel customers process more marketing messages and respond more frequently to marketing communications.

The extent to which customers alter their behaviors after adopting online channels likely differs across segments, because customers respond differently to marketing communications. Existing literature demonstrates that heavy shoppers are more responsive to advertising, price cuts, and coupons, because they can gain more from such promotions (Krishna, Currim, and Shoemaker 1991; Neslin, Henderson, and Quelch 1985; Vanhuele and Drèze 2002; Zhang, Seetharaman, and Narasimhan 2012). Moreover, heavy users exhibit higher shopping demand and can absorb additional quantities, because they tend to have larger families and live in larger houses (Neslin et al. 1985; Zhang et al. 2012). If customer behavior is mainly affected by marketing efforts, we propose an alternative hypothesis:

H*$_3$*: *Online firm channel adoption has more positive effects on the purchase volumes of heavy shopper segments than on those of light shopper segments.*

Self-selection. In order to accurately estimate the effect of online channel adoption, we should also consider the impact of customer self-selection. Customers with certain characteristics have intrinsic preferences for a particular channel (Boehm 2008; Konuş et al. 2008). The differences in characteristics between online adopters and offline customers also exist, such as age, education, and purchase level before online adoption (Neslin et al. 2006; Verhoef and Donkers 2005; Xue et al. 2011). Various studies show that ignoring such self-selection biases leads to inaccurate estimations of the effects of online adoption or use on customer behavior (Boehm 2008; Campbell and Frei 2009; Gensler, Leeflang, et al. 2012). Therefore, we employ a matching technique (i.e., propensity score matching; Dehejia 2005), to ensure a match in the characteristics of online adopters and offline customers.

Control variables. Finally, we control for several factors that could affect customer shopping behaviors: customer characteristics, previous purchases, competition, and time factors. Demographic characteristics include age and gender (Ansari et al. 2008; Xue et al. 2011). We also consider the effect of previous purchases on current purchases, known as state dependence or inertia (Rust, Lemon, and Zeithaml 2004; Valentini et al. 2011). Because our data span a long period, we control for the impact of time on customer spending, such as seasonality (Ansari et al. 2008; Pauwels et al. 2011). Finally, we control for the effects of external factors, such as competition and economic climate (recession), which could influence customer shopping behaviors and experiences (Van Diepen et al. 2009; Verhoef et al. 2009).

2.3. Data Description

2.3.1. Data

We used daily transactional data from a multichannel French retailer that sells healthy and natural products. With the aid of a French multichannel data-warehouse-consultancy company, we collected transactional data from competitors, namely, 16 French retailers competing in the same industry. Our data set thus contains individual transaction panels (i.e., transaction date, purchase amount, and transaction channel) from both the focal firm and its competitors. Transactions collected from competitors constituted 6.3% of total transactions, which we used to control for the effect of competition. This data set spans 12 years and seven months (151 months), from January 2000 to July 2012. The focal retailer had two established offline purchase channels (call center and catalog), then introduced a new online channel in January 2001. Thus, we had 1 year of observation prior to the online channel introduction and 11.5 years after, as Figure 2.2 details.

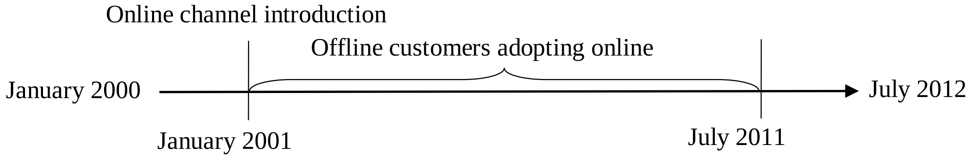

Figure 2.2: Timeline and Data Periods

To investigate the process by which existing offline customers adopt and evolve in relation to a newly introduced online channel, we selected a random set of 3,270 customers who had purchased from the retailer before the online channel introduction. All these customers started purchasing from the focal firm in the year 2000. In this set, 2,180 (66.7%) customers adopted the online channel by the end of the data period, whereas 1,090 remained offline customers did not adopt. We also used two additional criteria to select the final sample for analysis. First, so that we could examine the effects of online adoption on customer behavior, the online adopters had to have made purchases from this firm longer than one year prior to and one year after their online adoption. We thus identified a sample of 1,695 online adopters. Second, we excluded customers who terminated their shopping relationship with the firm in the early period, because our focus of interest is on the effect of online adoption on customer revenue, rather than customer churn. Specifically each selected customer had to purchase at least one time from the focal firm in the last two years, which excluded 45 online adopters and 105 offline customers. The selection procedure thus yielded a final sample of 1,650 online adopters who adopted the online channel between January 2001–June 2011 and 985 offline only customers. After adopting the online channel, 75.4% of online adopters continued to purchase from online channels, and 81% kept shopping through existing offline channels.

We provide the demographic descriptions and purchase information (from the focal firm) about the online adopters and offline customers in Table 2.1. In line with previous studies (Boehm 2008; Campbell and Frei 2009), on average, online adopters are younger (44 years) than offline customers (52 years). Online adopters' annual purchase amounts are lower (162.1 Euros) than the yearly purchases of offline customers (191.4 Euros), which conflicts with findings that indicate multichannel customers spend more than offline-only or single-channel customers (Neslin et al. 2006; Thomas and Sullivan 2005), but it is not abnormal for the health and natural products category. These product lines tend to be more expensive for older than younger shoppers, so the older, offline customers likely purchase larger volumes than younger, online adopters. Annual purchase amounts vary greatly across customers, from 13.8 to 2715.3 Euros for online adopters and 12.4 to1486.8 Euros for offline customers.

Table 2.1: Descriptive Statistics for Two Customer Groups

	Online Adopters			
Variable	**M**	**SD**	**Min**	**Max**
Age (in years)	44	10	20	91
Gender (female)	96.7%			
Purchases per year	1.9	1.9	0	23.0
Purchase amount per year (in Euros)	162.1	168.2	13.8	2715.3
Online adoption duration (in months)	73	28	3	124
Number of online purchases	5.6	9.3	1	165
	Offline Customers			
Variable	**M**	**SD**	**Min**	**Max**
Age (in years)	52	11	22	82
Gender (female)	97.1%			
Purchases per year	2.2	1.8	0	18.3
Purchase amount per year (in Euros)	191.4	154.3	12.4	1486.8

2.3.2. Outliers

To control for the effects of extreme outliers, we standardized the yearly purchase amounts for each customer and dropped customers with standard scores of 4 or greater (Hair et al. 2010). Thus we excluded 20 online adopters and 7 offline customers from the data set, yielding samples of 1,630 online adopters and 978 offline customers for the modeling.

2.3.3. Model-Free Evidence

We explored purchase volumes in customer groups who adopt online channels in different periods. Because the maximum adoption duration is 124 months, we equally divided this time length into three periods thus get three groups that adopt online in different times: early adopters (duration ≤ 40 months), middle-period adopters (40 months < duration ≤ 80 months), and late adopters (duration > 80 months). We summarize the average annual purchase amounts for these segments (see Table 2.2). The yearly purchase amounts were similar across segments, but different patterns emerged when we separated the amount spent prior to online channel adoption from the amount spent after it. In line with our expectations, early adopters spend more than other segments before adopting; however, late adopters generate more revenues per year after the adoption event. We cannot make inferences and draw conclusions from this preliminary analysis, but the model-free exploration suggests that various shopping patterns emerge among customer groups who adopt online channels at different times.

Table 2.2: Comparison of Purchase Amounts across Adoption Periods

	Adoption duration ≤ 40 months			**40 months < Adoption duration ≤ 80 months**		
Variable	**M**	**Min**	**Max**	**M**	**Min**	**Max**
Yearly purchase amount	148.1 (125.8)	20.8	1108.8	151.8 (152.4)	13	1623.6
Yearly purchase amount before adoption	156.4 (134.2)	10.2	853.3	133.1 (130.9)	1	1309.6
Yearly purchase amount after adoption	147.3 (147.0)	13.2	1482.7	170 (213.1)	12.8	2434.4

	Adoption duration > 80 months		
Variable	**M**	**M**	**M**
Yearly purchase amount	159.2 (188.8)	159.2 (188.8)	159.2 (188.8)
Yearly purchase amount before adoption	145.3 (179.4)	145.3 (179.4)	145.3 (179.4)
Yearly purchase amount after adoption	200.5 (272.7)	200.5 (272.7)	200.5 (272.7)

Notes: Values in brackets donate the standardized deviation.

2.4. Methodology

For our research purposes, our modeling process consists of three steps and a series of modeling methodologies. We first employ latent class cluster analysis (LCCA) to segment customers on the basis of their online adoption duration and purchase amount before adoption. In the next step, we use a propensity score matching (PSM) technique for each identified segment, to control for the effect of self-selection. Finally, by applying a Type II Tobit model and difference-in-difference (DID) analysis, we investigate the impact of online channel adoption on purchase volumes of different segments. Figure 2.3 summarizes the modeling purpose, corresponding method(s), and data format. The original data followed an unbalanced panel format, but we converted the data set into a cross-sectional or balanced panel format, depending on the requirement of each modelling purpose.

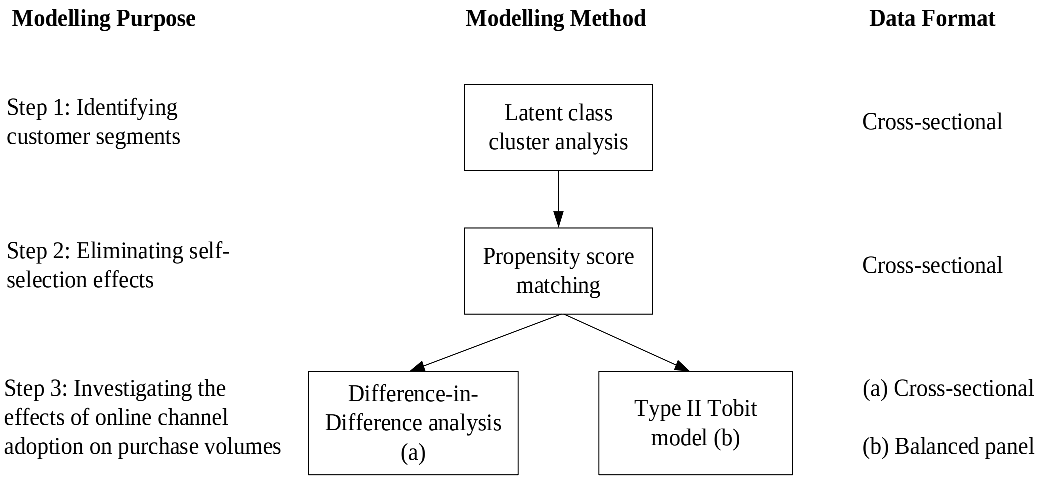

Figure 2.3: Summary of Modeling Approaches

2.4.1. Latent Class Cluster Analysis (LCCA)

We employed LCCA to investigate purchases by customers adopting a new online channel at different times. We segmented customers on the basis of online adoption duration and purchase amounts before adoption, while also considering the impact of covariates on customer membership (Vermunt and Magidson 2005), with the following model specification:

$$f\left(\boldsymbol{y}_i \middle| \boldsymbol{z}_i^{act\_cov}\right) = \sum_{x=i}^{K} P\left(x \middle| \boldsymbol{z}_i^{act\_cov}\right) \coprod_{j=1}^{J} f\left(y_{ij} \middle| x\right) \quad \text{(Eq. 2.1)}$$

where $\boldsymbol{y}_i$ denotes a set of J response variables (indicators) that measure customer i's response to the new online introduction, and y_j is a particular indicator. In our case, the indicators are adoption duration, and yearly purchase amount before adoption. The latent variable (x) is categorical, with K values, which corresponds to K segments. It is unnecessary to predict a priori the number of segments; rather, K is determined by the model selection criteria (Vermunt and Magidson 2002). Furthermore, $\boldsymbol{z}_i^{act\_cov}$ indicates a vector of active covariates (age and gender) that could affect the latent variable but have no direct influence on the response variables. We also included inactive covariates—*online shopping preference*[2] and *yearly purchase amount after online adoption*—to describe customers' behaviors of identified segments after adoption. As consequences of online channel adoption, these variables do not affect the latent variable or model estimation. Finally, $f(y_{ij}|x)$ represents the probability distribution of customer i's response to a particular indicator j, given that customer i belongs to segment x, and $f\left(\boldsymbol{y}_i \middle| \boldsymbol{z}_i^{act\_cov}\right)$ is the joint probability function of customer i's response to all indicators, as influenced by active covariates.

2.4.2. *Propensity Score Matching (PSM) Method*

A basic approach to test the effect of online channel adoption is to measure the changes in a customer's purchases after adoption (i.e., purchase incidence and

[2] With a random-effect logistic model, we calculate online shopping preference, that is, the probability that a customer shops through online versus offline channels in the period after the online adoption. The model function depends on the amount of the previous purchase on the online or offline channels, cumulative number of purchases on the online or offline channels before the current purchase, age, and gender.

order size), relative to a group of offline customers who do not adopt. We also need to address the potential impact of self-selection on customer shopping behaviors.

The most prominent methods to control for the self-selection bias are instrumental variable methods and matching methods (Boehm 2008; Heckman and Navarro-lozano 2004). The former methods seek to find appropriate instrumental variables, which must be exogenous and correlate with the binary treatment variable (e.g., online adoption) (Stock, Wright, and Yogo 2002; Wooldridge 2003). These strict requirements make it difficult to find valid instrumental variables, and weak instrumental variables lead to biases so severe that even a simple ordinary least squares regression using observed customer characteristics to control for selection would perform better (Woglom 2001). Instead, matching methods impose fewer restrictions and lead to more accurate estimations (Blundell, Dearden, and Sianesi 2005). The basic idea is to find matched samples (i.e., offline customers) whose customer characteristics are similar to those of the treated group (i.e., online adopters). Various matching techniques exist to build matched samples, including covariate matching, DID matching, and PSM (Abadie and Imbens 2006; Dehejia 2005; Zhao 2004). We used PSM to find a matched control group for each identified online adopter segment, such that the propensity score is the probability that a unit in the full sample receives the treatment, given a set of observed characteristics (Dehejia 2005). With this propensity score, we can ensure that the distribution of characteristics in the treated and matched groups is the same (Rosenbaum and Rubin 1983).

We used a binary logistic model to estimate the probability that a customer adopts the new online channel, as a function of purchase volumes prior to adoption (average monthly purchase frequency, average order size per transaction, or average monthly purchase amount), age (in years), gender, and tenure (in months). Because customers in the same segment could adopt the online channel in different periods, it is difficult to anticipate adoption duration for offline customers at this moment. We instead calculated previous purchase volumes in the period prior to the adoption of the earliest adopter in a segment. The control group comes from the data pool of the 978 offline customers, following the rules of one-to-one matching without replacement. Specifically, for each online adopter, we chose a matched offline customer who has the closest estimated propensity score. We also set up a caliper to guarantee that the absolute difference between the propensity of an online adopter and its matched offline customer is less than a certain threshold. With a common support restriction, we required all customers to lie within a region of common support (Heckman, Ichimura, and Todd 1997). This approach excludes online adopters with propensity scores smaller (larger) than the minimum (maximum) value of the propensity scores of the controls.

2.4.3. Difference-in-Difference (DID) Analysis

Using the matched samples, we tested the effects of online channel adoption in two complementary ways. A DID analysis compares the changes of customer behavior before and after the adoption event between treated (adopters) and control groups (Campbell and Frei 2009). Thus, we measured changes in terms of total purchase amount, total purchase frequency, offline purchase amount, and offline purchase frequency between one year prior to and one year after the adoption of online channels. The online adoption duration of an offline customer equals the adoption duration of the matched online adopter. If the changes in performances differ statistically between the group of online adopters and their matched offline customers, we conclude that online adoption significantly affects customer purchases. This simple DID method provides useful information about the effect of online adoption on behavioral changes, but it may not control adequately for differential postadoption trends between online adopters and the control group that result from factors that emerge over time (e.g., changes in previous purchase amounts, economy) (Campbell and Frei 2009).

2.4.4. Type II Tobit Model

To complement our DID analysis, we used a Type II Tobit specification to estimate the effects of online channel adoption on purchase incidence and order size over time. We assume that a customer first decides whether to purchase from the focal firm, and then decides how much to spend (i.e., order size) (Ansari et al. 2008). In this two-step modeling approach, we first employed a binomial probit model with random effects to determine whether a customer purchases from the focal firm in the current month—a dummy variable represented by P_{it}. Then, conditional on a purchase from the focal firm in a given month, we designed a regression model to determine the average order size per transaction, denoted by Q_{it} in our model. Similar to the DID analysis, we tested the effects of online adoption on customer behavior across segments, using the following model specifications:

$$P_{it} = \text{ Purchase, if } P_{it}^{*}>0\text{; No purchase, if } P_{it}^{*} \leq 0 \quad \text{(Eq. 2.2)}$$

$$P_{it}^{*} = \beta_0 + \beta_1 Post_{it} + \beta_2 Post_{it} \times Treated_i + \beta_3 Gender_i + \boldsymbol{X_{it}\gamma} + v_{it} \quad \text{(Eq. 2.3)}$$

$$Q_{it} = Q_{it}^{*} \text{, if } P_{it}^{*} > 0\text{; unobserved, if } P_{it}^{*} \leq 0 \quad \text{(Eq. 2.4)}$$

$$Q_{it}^{*} = \delta_0 + \delta_1 Post_{it} + \delta_2 Post_{it} \times Treated_i + \delta_3 Gender_i + \boldsymbol{X_{it}\theta} + \mu_{it} \quad \text{(Eq. 2.5)}$$

where P_{it}^{*} refers to the latent utility that customer i purchases from the focal firm in month t, and Q_{it}^{*} is the latent utility of the order size from the focal firm in month t. In addition, $Post_{it}$ is the key explanatory variable, equal to 1 for the period after customer i adopts the online channel in month t and to 0 if otherwise. Its coefficients (β_1 and δ_1) capture any changes in the purchases for the control group in the postadoption period. The dummy variable $Treated_i$ is 1 if customer i is the online adopter and 0 otherwise. The interaction between $Treated_i$ and

$Post_{it}$ measures the difference in the response variables between the treated and control group after adoption, thus revealing the effect of online adoption on customer behavior. $\boldsymbol{X_{it}}$ represents a vector of time-varying control variables, including age, several state dependent variables[3], purchase from competitors, recency, and seasonality. To mitigate seasonal influences, we adopt Ansari et al., (2008) method: (1) select monthly dummy variables that significantly affect monthly purchase frequency, then (2) combine the month dummies whose parameters do not significantly differ. We thereby identify four seasonality indicators: *March*, *August*, *April & May*, and *June & October*. We also consider the effect of the economic climate across the long period represented by our data set. In line with the periods of economic recession (Mostaghimi 2004; Ohanian 2010), we observe dramatic declines in the total number of transactions between 2001 and 2003 and between 2008 and 2010. A dummy variable (*Economic recession*) identifies these years. We summarize the measurements of above variables in Table 2.3.

[3] State-dependent variables are lagged variables that are defined differently in each equation. In Equation 3, which examines purchase incidence, the state-dependent variables are two dummy variables that indicate whether a customer shopped through the online channel or an offline channel in the last month. In Equation 4, which estimates order size, it is the order size of last purchase.

Table 2.3: Variable Measurements of Type II Tobit Model

Variable	**Measurements**
Postadoption	=1 if a customer has adopted the online channel before the current month; =0 otherwise
Treated group	= 1 if a customer is the online adopter; =0 otherwise
Past online purchase	=1 if a customer purchases through the online channel from the focal firm in the last month; =0 otherwise
Past offline purchase	=1 if a customer purchases through offline channels from the focal firm in the last month; =0 otherwise
Purchase from competitors	=1 if a customer purchases from competitors in the current month
Last order size	Amount of money a customer spent on the last purchase
Age	Age of a customer in the current month
Gender	=1 male; =0 female
Recency	Number of months since the last purchase.
Economic recession	=1 if current month is in 2001–2003 or 2008–2010; =0 otherwise
Seasonality 1: March	=1 if the current month is March; =0 otherwise
Seasonality 2: August	=1 if the current month is August; =0 otherwise
Seasonality 3: April & May	=1 if the current month is April or May; =0 otherwise
Seasonality 4: June & October	=1 if the current month is June or October; =0 otherwise.

2.5. Results

2.5.1. Results of Latent Class Cluster Analysis

Model selection. We start by presenting the LCCA results, which we estimated by applying solutions with different numbers of segments. Following Konuş et al. (2008), our model selection procedure relies on a set of statistical criteria: the Bayesian information criterion (BIC), Akaike information criterion (AIC), and Akaike information criterion with a penalty factor of three (AIC3), together with the interpretation of derived segments. Among the statistical criteria, we rely primarily on the BIC, because it is more effective for determining the correct number of segments for LCCA than are other criteria (Vermunt and Magidson 2005; Zhang 2004).

We provide the graphs for BIC, AIC, and AIC3 in Figure 2.4. The values of the three criteria are close and keep decreasing with more segments, but Figure 4 also suggests that the graphs of these indexes become flat after five segments. The estimated results are consistent across models with more than four segments; increasing the number of segments mostly enhances the complexity of the interpretation. Therefore, we chose the model with five segments, to balance the fit criteria and achieve an intuitive interpretation.

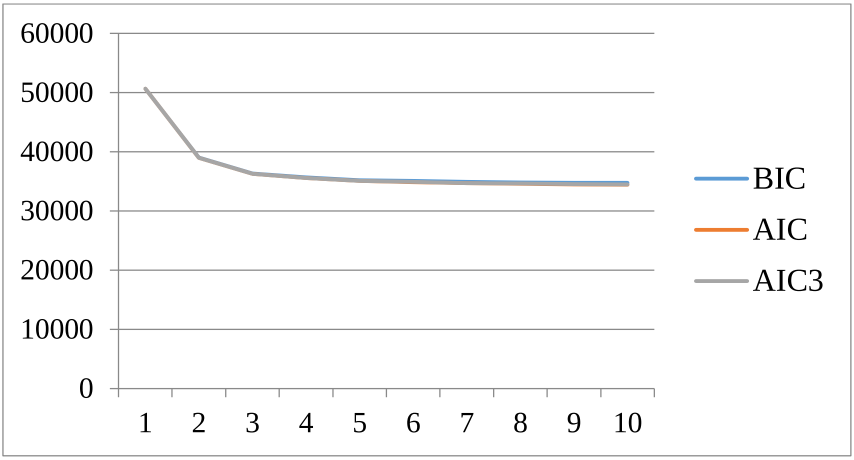

Figure 2.4: Graphs of Model Selection Criterion

Model profile. The results indicate a clear split of customer segments on the basis of their online adoption duration and purchase amount prior to online adoption. Tables 2.4 contains descriptive statistics for every identified segment. Because average adoption duration differs across the five segments—20 months, 47 months, 72 months, 92 months, and 101 months—we apply Rogers's (2003) segmentation framework and refer to the identified segments as innovators (181 customers), early adopters (311 customers), early majority (511 customers), late majority (170 customers), and laggards (457 customers), respectively.

Table 2.4: Profiles of Segments

Label	**Innovator** (N = 181, 11.10%)				**Early Adopter** (N = 311, 19.08 %)				**Early Majority** (N = 511, 31.35%)			
	M	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**
Indicators												
Adoption duration	20	6	3	30	47	8	31	65	72	8	56	87
Yearly purchase amount before online adoption	165.66	142.76	13.26	853.33	133.64	116.33	10.21	732.44	100.46	60.32	1.02	287.56
Covariates												
Age	44	8	21	68	44	10	20	76	43	9	20	70
Gender (male)	4.97%				5.79%				2.74%			
Yearly purchase amount after online adoption	139.86	102.57	15.19	710.65	144.05	117.88	12.79	730.2	140.41	115	13.78	794.21
Online shopping preference	0.622	0.104	0.205	0.857	0.596	0.124	0.124	0.843	0.589	0.103	0.199	0.805
Label	**Late Majority** (N = 170, 10.43%)				**Laggard** (N = 457, 28.04%)							
	M	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**				
Indicators												
Adoption duration	92	13	64	121	101	10	85	124				
Yearly purchase amount before online adoption	342.81	159.53	21.03	1041.3	80.63	46.91	5.94	207.44				
Covariates												
Age	51	11	24	91	43	9	22	88				
Gender (male)	1.76%				2.19%							
Yearly purchase amount after online adoption	331.15	223.34	28.67	1333.7	144.45	135.59	17.14	1088.94				
Online shopping preference	0.285	0.149	0.004	0.654	0.589	0.092	0.279	0.792				

The link between adoption duration and purchase amount before adoption is evident but different from our expectation: Prior to the adoption of online channels, the late majority segment on average spent 342.81 Euros per year, more than any other segments. Therefore, in contrast with H_1, the segment exhibiting the most intensive shopping behavior is not the earlier adopters but rather the late majority. The results for other four segments instead match our expectations, such that innovators (165.66 Euros) and early adopters (133.64) spend more than the early majority (100.46 Euros) or laggards (80.63 Euros) prior to their adoption of online channels.

After the adoption of online channels, most segments make more purchases, though innovators and the late majority reduce their spending slightly, from 165.66 to 139.86 Euros per year and from 342.81 to 331.15 Euros per year, respectively. With respect to online shopping preferences, the late majority segment exhibits the lowest preference (.285) for shopping online, rather than the laggards. The average age of members of the late majority is approximately 51 years, older than other four segments whose average ages range between 43 and 44 years. The late majority segment also is least likely to include men (1.76 %) compared with the other segments. For other segments, there are greater proportions of men in earlier adopter segments compared with later adopter segments, which is in line with previous studies (e.g., Venkatesan et al., 2007).

Parameter estimation. Table 2.5 contains the parameter estimations for the indicators and active covariates in the LCCA. Two indicators are statistically significant ($p < .01$) in most segments, suggesting that they effectively cluster the customer segments.

Table 2.5: Parameter Estimation of Latent Class Cluster Model

	Innovator	Early Adopter	Early Majority	Late Majority	Laggard	Wald	*p*-Value (Wald)
Indicators							
Adoption duration	-1.075***	-0.193***	0.226***	0.476***	0.566***	6144.5	0.000
Yearly purchase amount before adoption	10.8	-24.2***	-56.6***	146.0***	-75.9***	284.7	0.000
Active Covariates							
Age	-0.002	-0.010*	-0.017**	0.051***	-0.022***	442.6	0.000
Gender (male=1)	0.232	0.330*	-0.055	-0.343	-0.164	95.4	0.049

***Significant at .001. **Significant at .01. *Significant at .05.

With respect to the covariates, the Wald test indicates that the age ($p < .001$) and gender ($p < .05$) coefficients differ significantly across segments. Age has a positive effect on the probability of being in the late majority (.051, $p < .001$) but a negative effect on the likelihood of being in other segments: early adopter (-.010, $p < .05$), early majority (-.017, $p < .01$), or laggard (-.022, $p < .001$). Male customers are more likely to be early adopters (.330, $p < .05$); however, gender does not affect membership in other segments. These results are consistent with findings in Table 2.4.

Summary. We segment customers on the basis of their adoption duration and yearly purchase amounts before online channel adoption. The average spending levels differ across these segments, and in most cases, age significantly affects membership. Our main finding at this stage is that the customers who spend the most, both before and after online channel adoption, are not the early adopters of a new online channel but rather the late majority, who adopt the online channel in a middle to late period. These customers exhibit unique shopping patterns and characteristics that distinguish them from adjacent segments: They are the oldest customers on average, most likely to be women, and exhibit the lowest online shopping preference. Besides, innovators and early adopters spend more than the early majority and laggard segments prior to their adoption of online channels. Moreover, the extent to which purchase volumes change after online channel adoption varies across segments.

2.5.2. Results of Propensity Score Matching Method

Our matching technique seeks to link an online adopter in a segment with an offline customer who has a similar propensity to adopt the online channel, so that we can account for self-selection. We used a logistic model to calculate a customer's propensity to adopt the online channel, given the set of character variables. In each segment, we chose the predictor variables that generated the best model fit, and in Table 2.6, we present the estimations of the parameters for five segments.

Table 2.6: Parameter Estimation of Propensity Score Model

	Innovator	**Early Adopter**	**Early Majority**	**Late Majority**	**Laggard**
Age	-0.088	**-0.067**	**-0.079**	**-0.008**	**-0.080**
Age^2	**-0.003**	0.000	**-0.001**	0.000	**-0.001**
Gender (male=1)	0.664	**0.667**	0.056	-0.331	-0.061
Tenure	-0.013	0.038	-0.017	-0.008	0.015
Previous monthly purchase amount	-	-	**-0.085**	-	-
Previous monthly purchase frequency	-0.884	**-2.702**	-	**3.463**	**-14.417**
Previous order size per transaction	**-0.001**	0.003	-	**0.008**	-0.002
Constant	-1.301	**-2.670**	1.334	**-1.987**	-0.402

Notes: Bold values are significant at the .05 level.

As we explained in the methodology section, we employed a common support restriction and set our caliper to .01 to establish the minimum difference allowed with respect to the estimated propensities between an online adopter and the matched offline customer. This restriction excluded 1 (.55%) of 181 innovators, 29 (9.32%) of 311 early adopters, 84 (16.44%) of the 427 early majority, 9 (5.29%) of the 170 late majority, and 113 (24.73%) of 457 laggards.

Table 2.7: Significance of Difference and Reduction in Bias after Matching

	Innovator	**Early Adopter**	**Early Majority**	**Late Majority**	**Laggard**
	Significance of Difference				
Age	0.548	0.712	0.423	0.722	0.771
Gender	0.793	0.664	1.000	1.000	1.000
Tenure	0.557	0.717	0.520	0.843	0.991
Previous monthly purchase amount	-	-	0.204	-	-
Previous monthly purchase frequency	0.432	0.869	-	0.647	0.500
Previous order size per transaction	0.689	0.356	-	0.185	0.680
	Reduction in bias (%)				
Age	92.8	96.1	94.4	38.8	97.8
Gender	72.3	74.9	100.0	100.0	100.0
Tenure	7.5	40.6	65.6	51.7	98.8
Previous monthly purchase amount	-	-	91.9	-	-
Previous monthly purchase frequency	63.5	96.8	-	93.9	97.3
Previous order size per transaction	-69.3	21.1	-	13.5	-196.6

To qualify the performance of our matching procedure, we first checked if the differences in customer characteristics remained statistically significant after matching, using a t-test, then computed the percentage of bias reduction (Rosenbaum and Rubin 1985) (see Table 2.7). The reduction in bias represents the difference in the mean of a particular characteristic between two matched groups after matching, minus the difference before matching (Rosenbaum and Rubin 1985). The percentage of bias reduction was substantial for most characteristics. Only the metrics of previous order size were negative for certain segments, suggesting that the two groups became less comparable on this factor after matching. However, an increase in bias for this variable would not affect overall matching performance, because the differences between online adopters and matched offline customers were not significant for all customer characteristics after matching. Therefore, the samples were comparable after matching, and we eliminated self-selection bias concerning the selected characteristics with our PSM method.

2.5.3. Results of Difference-in-Difference Analysis

Tables 2.8 contains the results of the DID analysis, which are estimates of the differences in the mean of purchase activities, aggregated in the one-year periods prior to and after the adoption of online channels. For the early adopter, early majority, and laggard segments, total annual purchase amounts and frequencies significantly increase after online channel adoption, and the difference metrics are significantly larger than the changes for the matched offline customers. These results suggest that online channel adoption is positively associated with purchase volumes in these segments. Moreover, the changes in the offline purchase amounts and frequencies after online channel adoption are not significant in these segments, suggesting that increases in customer spending derive from additional demand through the new online channel, rather than substituting for purchases in existing offline channels. However, the changes in the purchase volumes in the innovator and late majority segments do not differ significantly from the variation of purchases in the control groups. Innovators increase their purchases significantly after adopting online, but these increased amounts do not significantly differ from those in the control group. Furthermore, both segments reduce their offline purchase amounts and frequencies after adopting online channels. Thus, online channel adoption has no effect on the purchase amounts or frequencies of innovators and the late majority. Thus, results of the DID analysis support H_2, which suggests that online channel adoption exerts more positive effects on the purchase volumes of light shopper segments than of heavy shopper segments.

Table 2.8: DID Analysis

	Online Adopters			Offline Customers		
	Before	**After**	**Change**	**Before**	**After**	**Change**
Innovator						
Total purchase amount	122.76	146.48	23.72*	122.48	135.54	13.07
(in Euros)	(160.96)	(183.11)	(13.59)	(176.52)	(173.43)	(221.79)
Total purchase frequency	1.32	1.63	0.32*	1.31	1.38	0.07
	(1.63)	(1.85)	(1.90)	(1.87)	(1.54)	(2.11)
Offline purchase amount	122.76	64.83	-57.93*			
(in Euros)	(160.96)	(116.39)	(163.82)			
Offline purchase frequency	1.32	0.72	-0.60*			
	(1.63)	(1.12)	(1.57)			
Early adopter						
Total purchase amount	113.28	158.83	45.54*#	140.70	153.54	12.85
(in Euros)	(155.29)	(217.52)	(213.71)	(176.64)	(174.82)	(195.51)
Total purchase frequency	1.23	1.96	0.74*#	1.58	1.83	0.25
	(1.65)	(2.75)	(2.66)	(1.86)	(2.17)	(2.14)
Offline purchase amount	113.28	95.99	-17.29			
(in Euros)	(155.29)	(161.08)	(176.30)			
Offline purchase frequency	1.23	1.15	-0.08			
	(1.65)	(2.02)	(2.04)			
Early majority						
Total purchase amount	94.82	183.54	88.72*#	125.01	126.73	1.72
(in Euros)	(133.37)	(259.05)	(254.96)	(192.67)	(184.99)	(217.68)
Total purchase frequency	1.13	2.04	0.90*#	1.44	1.48	0.04
	(1.55)	(2.98)	(2.85)	(2.24)	(2.08)	(2.31)
Offline purchase amount	94.82	106.64	11.82			
(in Euros)	(133.37)	(204.17)	(215.39)			
Offline purchase frequency	1.13	1.14	0.01			
	(1.55)	(2.31)	(2.33)			

	Online Adopters			Offline Customers		
	Before	**After**	**Change**	**Before**	**After**	**Change**
Late majority						
Total purchase amount	383.55	347.01	-36.53	246.75	255.52	8.78
(in Euros)	(326.14)	(308.74)	(354.04)	(292.69)	(394.04)	(406.89)
Total purchase frequency	4.37	4.20	-0.16	2.88	2.89	0.02
	(3.61)	(3.78)	(3.93)	(3.28)	(3.71)	(3.58)
Offline purchase amount	383.55	268.55	-115.00*			
(in Euros)	(326.14)	(284.85)	(338.02)			
Offline purchase frequency	4.37	3.20	-1.16*			
	(3.61)	(3.39)	(3.62)			
Laggard						
Total purchase amount	71.22	133.26	62.04*#	98.05	101.38	3.33
(in Euros)	(124.30)	(264.82)	(276.16)	(170.77)	(157.32)	(168.38)
Total purchase frequency	0.83	1.65	0.82*#	1.16	1.31	0.15
	(1.37)	(2.56)	(2.63)	(1.82)	(1.88)	(1.96)
Offline purchase amount	71.22	69.68	-1.54			
(in Euros)	(124.30)	(153.80)	(168.43)			
Offline purchase frequency	0.83	0.85	0.02			
	(1.37)	(1.50)	(1.60)			

Notes: This table provides the means, with the standard deviations in brackets.
*Significantly different from 0 at least at the 10% level.
#The change in the variable for online adopters is significantly different from the change for offline customers (control group) at least at the 10% level.

2.5.4. Results of Type II Tobit Model

We employed the Type II Tobit model to investigate the effects of online channel adoption on monthly purchase incidence and order size per transaction across different segments over time. Customers from different segments adopt online channels at different times (month 4 to month 124), so the period prior to and after online adoption varies greatly. For a fair comparison across segments, we tested the models using the same length of time (one year) prior to and after online adoption. Therefore, the tested data contain 24-month observations for each customer. Table 2.9 and 2.10 present results of the Type II Tobit model.

Table 2.9: Purchase Incidence Model (24 months)

Variable	Innovator	Early Adopter	Early Majority	Late Majority	Laggard
Postadoption	0.063	0.076	0.070*	-0.084	0.087*
Postadoption × Treated group	-0.032	-0.032	0.157***	0.021	0.041
Past online purchase	0.070	0.199**	0.142*	0.158*	0.321***
Past offline purchase	-0.009	0.110*	0.190***	0.039	0.079
Purchase from competitors	0.028	0.430*	0.232	0.321**	0.177
Age	0.006	0.005*	-0.002	0.005	0.003
Gender	-0.062	0.035	0.092	0.044	-0.158
Recency	-0.016***	-0.008***	-0.006***	-0.022***	-0.009***
Economic recession	-0.131	-0.155**	-0.060	-0.045	-0.029
Seasonality 1: March	0.303***	0.298***	0.291***	0.331***	0.230***
Seasonality 2: August	-0.070	-0.242***	-0.136**	-0.090	-0.032
Seasonality 3: April & May	0.080	0.009	0.060	-0.026	0.048
Seasonality 4: June & October	0.122*	-0.029	0.036	0.092	0.083
Constant	-1.464***	-1.491***	-1.372***	-0.993***	-1.610***

***Significant at .001. **Significant at .01. *Significant at .05.

Table 2.10: Order Size Model (24 months)

Variable	Innovator	Early Adopter	Early Majority	Late Majority	Laggard
Postadoption	0.506	-2.343	5.981	-1.635	-7.500*
Postadoption × Treated group	-6.724	-2.889	11.776**	-0.449	4.053
Last order size	0.169***	0.103***	0.129***	0.163***	0.176***
Age	-0.335	0.310	-0.036	-0.294	0.021
Gender	0.509	7.372	-3.424	-2.964	-11.730
Recency	1.687	-0.165	-0.101	-0.286	0.026
Economic recession	17.164	-0.656	-16.856***	-5.173	5.111
Seasonality 1: March	-20.220	9.875	0.369	12.462	-4.397
Seasonality 2: August	12.320	-3.623	-8.751	-2.499	-1.774
Seasonality 3: April & May	4.734	2.965	-5.244	-6.112	0.936
Seasonality 4: June & October	-7.833	3.577	-8.371*	1.699	61.264
Constant	241.083	-2.209	6.576	50.318	3.238

***Significant at .001. **Significant at .01. *Significant at .05.

Parameter estimates of the interaction between the postadoption period and the treated group reveal significant and positive effects on purchase incidence (.157, $p < .001$) and order size (11.776, $p < .01$) among the early majority; these customers increase their monthly purchase volumes after adopting online channels, relative to the control group, consistent with the DID analysis. However, the interactive effects are not significant for the other segments, suggesting online channel adoption has no impact on the monthly purchases of these segments. The findings related to early adopters and laggards understandably differ from those in the DID analysis that reveals positive effects of online adoption, because the changes in purchase volumes due to online channel adoption likely are more exaggerated in a DID analysis than a Tobit model. The DID analysis measures changes in the yearly purchase volume after adoption, whereas the Tobit model evaluates changes in monthly purchase volumes over time. The insignificant effects of online channel adoption for the innovator and late majority segments instead are consistent with the DID analysis, which confirms our prediction in H_2 but is contrary to H_3. These combined findings indicate that customer behavior is driven predominantly by the intrinsic benefits of online shopping.

For the control variables, we find that purchases from online channels in the previous month exert positive effects on purchase incidence in most segments, with the exception of innovators. Offline purchases in the previous month enhance purchase probabilities among the early adopter (.110, $p < .05$) and early majority (.190, $p < .001$) segments. The order size of the previous transaction relates positively to the amount spent in the current transaction in all segments. Purchase from competitors in the current month affects the purchase incidence of the early adopters (.430, $p < .05$) and the late majority (.321, $p < .01$), suggesting higher category demand. Age only affect the purchase incidence of early adopters (.005, $p < .05$) and we find no significant gender effects. Furthermore, recency has significant, negative effects on purchase incidence in all segments, which may reflect a feature of the beauty and healthy category, for which purchase frequency is relatively lower than in most consumer goods industries (Inman et al. 2004). In our study, customers purchase from the firm twice per year on average. Because the average period between purchases is long, it might be difficult for customers to recall the firm or brand from which they bought previously, and their purchase patterns could be interrupted easily. Therefore, the longer the time since their last purchase, the less likely customers may be to purchase from the focal firm. Periods of economic recession relate negatively to the probability of purchase, but this effect is only significant for early adopters (-.155, $p < .01$). With respect to seasonality, we find that customers in all segments increase their purchase frequencies in March, but this factor does not affect the amount spent per transaction.

Result summary. The main findings of the DID analysis and Tobit model reveal that the effects of online channel adoption on customer purchases varies vary across segments. Online channel adoption increases monthly purchase incidence, order size, yearly purchase amounts, and yearly purchase frequency for the early majority segment, but it has no effect on purchases by innovators or the late majority. For early adopters and laggards, the results of the DID analysis suggest that customers increase their purchase amounts and frequencies, aggregated at the yearly level, but the influence is not significant on a monthly basis.

2.5.5. Robustness Checks

Several additional analyses enable us to test the robustness of the estimated effects. First, we examined the effects of online adoption on purchase incidence and order size in longer periods: two years prior to and after online channel adoption (four years total) and three years prior to and after online channel adoption (six years total). We repeated the DID and Tobit II analyses but only for the early adopter and early majority segments; the data periods for the other segments were too short either before (innovator) or after (late majority and laggard) the online adoption date. The results in Table 2.11 reveal that though early adopters purchase more in the postadoption period, the variation in their purchase frequency and order size per transaction do not significantly differ from the changes exhibited by the control group in either the four- or six-year time windows. Consistent with our initial analysis, online channel adoption significantly increases purchase incidence (.092, $p < .001$) and order size (6.092, $p < .05$) in the early majority segment, relative to the control group, in the four-year period. In the six-year time window, the purchase incidence change is not significant for the early majority versus control group of offline customers. However, the order size increase is significantly larger than that displayed by the control group (3.489, $p < .05$). Thus, the early majority segment increases its monthly purchase amount after adopting the online channel, and these results are robust across various periods.

Second, we tested whether our models are sensitive to extreme values by including the outliers that we deleted previously, then repeating the modeling process (detailed results are in Appendix A). Some minor differences arose, but the estimated results of the full data set are very consistent with our main findings. Third, we checked the results related to the late majority segment, because the standardized deviations of purchase amounts before and after online adoption were much larger than in the other groups. To eliminate the influence of extreme values, we excluded the 5% customers with the greatest purchase amounts and the 5% customers with the lowest purchase amounts before or after online adoption. With these two selection rules, we dropped 15 customers in total, then replicated the analyses. The results of the DID analysis and Type II Tobit model both suggest that online channel adoption has no effect on customer purchase volumes in this segment (see Appendix B), which confirms our previous findings.

Table 2.11: Purchase Incidence-Order Size Model (48 Months and 74 Months)

	48 Months				72 Months			
	Purchase Incidence		Order Size		Purchase Incidence		Order Size	
Variable	**Early Adopter**	**Early Majority**	**Early Adopter**	**Early Majority**	**Early Adopter**	**Early Majority**	**Early Adopter**	**Early Majority**
Postadoption	0.087**	0.080**	2.429	8.247***	0.104***	0.132***	2.194	7.708***
Postadoption × Treated group	-0.003	0.092***	0.916	6.092*	-0.020	0.019	-1.058	3.489*
Past online purchase	0.239***	0.188***	--	--	0.226***	0.213***	--	--
Past offline purchase	0.101**	0.217***	--	--	0.144***	0.200***	--	--
Purchase from competitors	0.330*	0.142	--	--	0.281***	0.151	--	--
Last order size	--	--	0.149***	0.142***	--	--	0.145***	0.138***
Age	0.004*	-0.001	0.236*	0.013	0.003	-0.001	0.186	-0.065
Gender	0.011	0.010	5.233	-2.306	-0.012	-0.012	5.312	-2.084
Recency	-0.008***	-0.004***	-0.266	-0.121	-0.009***	-0.005***	-0.283	-0.064
Economic recession	-0.132***	-0.081***	4.040	-15.097***	-0.111***	-0.117***	-0.998	-12.746***
Seasonality 1: March	0.288***	0.261***	11.309*	2.387	0.260***	0.247***	9.446*	-0.055
Seasonality 2: August	-0.192***	-0.113**	-6.917	-3.817	-0.160***	-0.101***	-6.132	-3.943
Seasonality 3: April & May	0.034	0.065*	3.140	-1.746	0.030	0.061**	1.711	-0.730
Seasonality 4: June & October	0.022	0.024	1.873	-6.187**	0.054*	0.032	2.287	-4.236*
Constant	-1.472***	-1.377***	-21.961	5.567	-1.445***	-1.349***	-21.584	19.679

***Significant at .001. **Significant at .01. *Significant at .05.

2.6. Discussion and Implications

We segment customers on the basis of online adoption duration and purchase amounts before the adoption and explore their purchase amounts and frequencies. We also investigate the effects of online channel adoption on customer purchases across multiple segments over time. For this discussion, we address the two research questions that motivated our study.

2.6.1. Theoretical Implications

Do Earlier Adopters of a Retailer's Online Channel Purchase More?

Briefly, no. Our results instead reveal that customers in the late majority segment purchase more than the other segments, both before and after they adopt the new online channel. Previous literature describes later adopters as having less income, lower education levels, and less involvement in a newly adopted new product or service (Mahajan, Muller, and Srivastava 1990; Prins and Verhoef 2007; Rogers 2003). Our research suggests additional features that differentiate it from others. Customers in this late majority segment exhibit the lowest online shopping preference and are more likely to be women and older than those in other segments. Yet the late majority still is the most valuable segment. We explain why with two sub-questions.

Why are heavy shoppers the late majority in their adoption of online channels? The multichannel environment helps answer this question. In this study, the firm's existing customers gradually adopted a newly introduced online channel, so they had purchased through the retailer's offline channels (catalog, telephone) prior to adopting the online channel. Heavy shoppers bought with higher frequency and volume through these offline channels, which might suggest they perceive offline shopping as more convenient than do other customers. Moreover, positive shopping experiences in a channel increase channel loyalty (Ansari et al. 2008), especially if customers initiate their purchase process through offline channels (Dholakia, Zhao, and Dholakia 2005; Gensler et al. 2007). Thus, heavy shoppers might tend to keep shopping through their preferred, existing, offline channels and delay their adoption of a new online channel. Yet they are not laggards, because their frequent interactions with the firm quicken the rate at which they develop trust in it and form their perceptions of the benefits of this firm's products or services (Hinde 1979; Morgan and Hunt 1994). Therefore, purchase frequency shortens the time needed to adopt additional channels (Venkatesan et al. 2007). Furthermore, customers' expenditures cultivate their firm loyalty, which also speeds up the adoption process (Demoulin and Zidda 2009). Facing conflicting mechanisms, these customers do not adopt immediately after the introduction of the online channel (due to channel loyalty), but nor do they take the longest time to start online shopping (due to trust and firm loyalty). Instead, they adopt the online channel in a middle–late period.

Why do heavy shoppers purchase less from the online channel after adopting it? Customers' channel choices evolve over time, as they learn from previous usage experiences (Konuş et al. 2014; Valentini et al. 2011). Customers become less responsive to marketing and less likely to move to new channels when they know more about the firm's established channels (Valentini et al. 2011), which may explain why customers in the late majority segment make few online purchases after adopting the channel. They already make more purchases through existing offline channels, so they are more knowledgeable about offline channels and less responsive to marketing efforts that encourage uses of the new online channel. Empirical evidence affirms that heavy shoppers exhibit greater loyalty to sales channels than light shoppers and are less likely to switch to different channels (Gensler et al. 2007). Thus, our study confirms that it remains difficult to move heavy shoppers from existing sales channels to a new channel, even after they adopt this new channel.

Are earlier adopters not valuable? Compared to most adopter segments, earlier adopters remain valuable, although their purchase volumes are lower than those of the late majority segment. Innovators and early adopters who adopt a new online channel in the early period purchase more than late adopters (early majority and laggard), prior to their adoption of a new online channel. These findings are consistent with our expectations and previous channel adoption research (Venkatesan et al. 2007; Xue et al. 2011). Thus, earlier adopters are valuable with respect to the revenues they generate.

How Does Online Channel Adoption Affect Purchase Volumes Across Segments? The effects of online channel adoption on customer purchases vary across segments. These effects differ particularly between the heavy and light shopper segments.

- *Heavy shoppers.* Heavy shopper segments are the innovators and late majority, who are the heaviest shopping segments prior to the adoption of the new online channel. Their online channel adoption has no effect on their purchases, in terms of monthly purchase incidence, order size, yearly purchase amount, or yearly purchase frequency. Customers in these two segments simply move a proportion of their demand from existing offline channels to the new online channel. Therefore, the new online channel cannibalizes purchases from offline channels in these segments.
- *Light shoppers.* Customers in the early adopter, early majority, and laggard segments increase their yearly purchase amounts and frequencies after adopting online channels (DID analysis), but only the early majority segment increases its monthly purchase incidence and order size over time (Type II Tobit analysis). According to the DID analysis, customers in light shopper segments tend to purchase the same amount offline after adopting online channels, so the additional volumes appear to derive mainly from sales in the new online channel.

Overall, heavy shopper segments are less affected by their adoption of online channels than are light shopper segments. Although customer behavior can be driven by intrinsic benefits and by marketing communications (Ansari et al. 2008; Neslin et al. 2006), our findings suggest that the benefits of online shopping represent the predominant influence on customer purchases after they adopt online channels. Heavy shoppers establish stronger purchasing habits in existing offline channels than light shoppers (Aarts et al. 1998; Orbell et al. 2001), so they may perceive fewer benefits from online shopping than do light shoppers (Falk et al. 2007). As a result, these customers view the online channel as a simple extension of distribution channels, which does not affect their overall shopping demand. The findings related to the light shopper segments also support this interpretation. These light shoppers perceive more benefits from online shopping and consider the new online channel an additional benefit, beyond offline channels. They reward the firm for this extra benefit by increasing their spending, mostly coming from the online channel. Furthermore, customers' share-of-wallet might also affect purchase volumes between light and heavy shopper segments after their adoption. Compared to light shoppers, company may have a higher share-of-wallet among heavy shopper segments. Since customers only need a certain amount of groceries, it is more difficult to gain extra sales from heavy buyers than light shoppers after online channel adoption. The study of Liu (2007) supports this argument, proving that light buyers purchase more frequently and become more loyal to firms after adoption of a loyalty program, whereas the spending levels and loyalty of heavy shoppers do not change over time.

2.6.2. Managerial Implications

Because the effect of online channel adoption varies across segments, retail managers should differentiate their strategies to appeal to two specific groups: a combination of early adopter, early majority, and laggard segments, and then a combination of innovators and late majority. In the former group, customers are more responsive to the online channel and increase their overall purchase volumes through the new channel, without reducing purchase volumes in offline channels. Therefore, retailers should focus on stimulating their online shopping volumes. For example, they could increase the frequencies of firm–customer interactions that promote online spending by these customers.

Furthermore, retailers should actively work to switch most purchases by these customers to the cost-saving online channel, to reduce their overall service costs. In contrast, for the latter group of customers (innovators and late majority), the overall purchases do not increase after adoption. Instead, they replace their offline purchases with online purchases. These heavy customers are likely habitual shoppers in the retailer's existing offline channels and are less likely to view online shopping as a benefit. Thus, instead of pushing them to shop online (i.e., by sending more advertisements), retailers should work on facilitating their perceptions of the benefits of online shopping, such as by promoting its high quality or emphasizing its benefits. Yet retailers cannot take the risk of ignoring their profitable contacts with these customers through existing offline channels.

2.6.3. Limitations and Further Research Directions

This research has several limitations that provide ideas for ongoing research. First, limited by data availability, we lacked information about the marketing activities that the focal retailer launched through its three channels. Therefore, we detect the effects of marketing on customer purchases only through indirect inferences. Additional research may investigate the effects of multichannel communications on customers' behaviors across segments that adopt online in different periods.

Second, we focused on purchase amounts and frequencies rather than profitability, because we cannot access unit product costs or service costs. Retailers use customer profitability as a key metric for evaluating the monetary value of their individual customers, so further research could explore customer profitability across segments and address the effects of online channel adoption on customer profitability for these different segments.

Third, we did not distinguish different product categories or types, due to data limitations. Customer multichannel shopping behavior and the effects of online channel adoption differ across product categories (Konuş et al. 2008; Kushwaha and Shankar 2013; Pauwels et al. 2011). As Gensler et al. (2012) reveal, frequently used products benefit more from online channel use than do infrequently used products. Therefore, future studies could replicate our research in other categories.

Fourth, our data set did not contain information about attitudinal or psychographic features and offered limited demographic information. Including more such information could help firms identify and characterize customer segments. Therefore, additional research should include more covariates that reflect customer attitudes about multiple channels, psychographic traits, and demographic information, such as income or occupations.

Last but not the least, the study period spans the time frame when the Internet channel became more sophisticated over time, which could have played a role in the observed results. Of course, this is a characteristic of all newly emerging channels and thus the results can provide useful generalizations. But still, further research could conduct similar studies to understand customers' adoption of other new channels, such as mobile channels and social media.

CHAPTER 3

Customer Channel Migration in the Competitive Environment: The Effects of Cross-Channel Competition[4]

Customers switch among multiple channels offered by different firms, so multichannel shopping behavior also depends on the channels offered by competitors. This important issue remains largely untapped by marketers and managers though. This study investigates the impact of customers' past and current purchases from competitors' channels on channel choices with a focal firm that introduces a new online sales channel, as well as the effect of new online channel adoption on purchase volumes from the focal firm and its competitors. The data contain eight-year individual transactions from ten competitive multichannel home décor retailers. Each customer has a unique identity that is identical across all retailers. Our research reveals that customers' previous purchases from competitors' online channels promote the probability of online channel adoption. This effect is greater for existing customers than new customers who are acquired after the introduction of the new online channel. Customer adoption and use of this new online channel reduce purchase frequencies of competitors, but increase purchase frequencies of the focal firm, for both existing and new customers.

[4] This chapter is under review in the *International Journal of Electronic Commerce* as: Li, J., Konuş, U., Langerak, F., Weggeman, M.C.D.P.: Customer Channel Migration and Firm Choice in a Competitive Environment: The Effects of Cross-Channel Competition.
Earlier versions of this study have been presented at 2013 European Marketing Academy Conference (Istanbul, Turkey) and 2012 Informs Marketing Science Conference (Boston, U.S.).

3.1. Introduction

Traditional retailers are expanding their business to online markets. The Internet has become a mainstream sales channel. The online retail sales in U.S. occupied 9% of the $3.2 trillion total retail market in 2013 and will continue to grow at an annual growth rate of nearly 10% through 2018 (Forrester Research 2014c). European online retail sales will grow at a rate of 12% per year by 2018 (Forrester Research 2014b). However, plenty of offline retailers have not yet adopted or even planned to introduce an online sales channel. In the multichannel environment, customers can shop from multiple channels offered by competitive firms. Prior to a late entrant introducing its own online channel, customers might have already had similar online shopping experience from competitors' online channels as well as offline shopping experiences from competitors, which could influence their overall channel preference. Therefore, the late entrant that enters the online market further behind its competitors faces greater challenges than early entrants, because customers' previous purchase or use experiences with competitors' channels might affect their migration to the Internet. Besides, customers could simultaneously switch firms when they switch channels (Dholakia et al. 2010). In this sense, a new online channel creates cross-channel competition in the online channel context it shares with competitors, as well as other offline channels used by competitors.

In such an environment firms must understand the effects of cross-channel competition on customer channel migration. Practical reports show that multichannel shoppers constitute 86% of the consumer market (PricewaterhouseCoopers 2011) and spend approximately 82% more per transaction than the customers who only shop in stores (Rigby 2014). Empirical findings also suggest that multichannel customers buy substantially more and are more valuable than single-channel users (Ansari et al. 2008; Thomas and Sullivan 2005). Managers thus need to have a clear knowledge about how customers choose and migrate among multiple channels, especially in a competitive multiretailer setting. Existing literature indicates that prior channel usage greatly affects subsequent channel choice and migration (Ansari et al. 2008; Inman et al. 2004; Montoya-Weiss et al. 2003), and customer shopping behavior depends on competitors' marketing actions (Van Diepen et al. 2009; Moe and Yang 2009; Prins and Verhoef 2007). However, most studies consider only the effects within the same firm or general channel usage, without distinguishing between channel usage for a firm that introduces a new channel and its competitors. Therefore, as emphasized by Neslin and Shankar (2009), it is still unknown whether customers perceive the same channel differently from the focal firm to competitors and how customers' previous purchases from competitors' online and offline channels affect customer migration to the new online channel introduced by a focal firm (see Figure 3.1). Furthermore, it is necessary to distinguish between a firm's existing customers and the new customers who are acquired by the firm after the introduction of an online channel, because their channel preference and their reactions towards a new online channel could be different. For example, Valentini et al. (2011) illustrate that certain existing customers are less responsive to marketing and less likely to switch channels than newly acquired customers. Avery et al. (2012) differentiate between first-time and repeat customers, and suggest that the effects of a brick-and-mortar store on the sales of direct channels differs between the two customer groups. However, it is not clear whether cross-channel competition affects channel migration of above customer groups differently. In response, we investigate the effects of cross-channel competition on channel migration of existing and new customers.

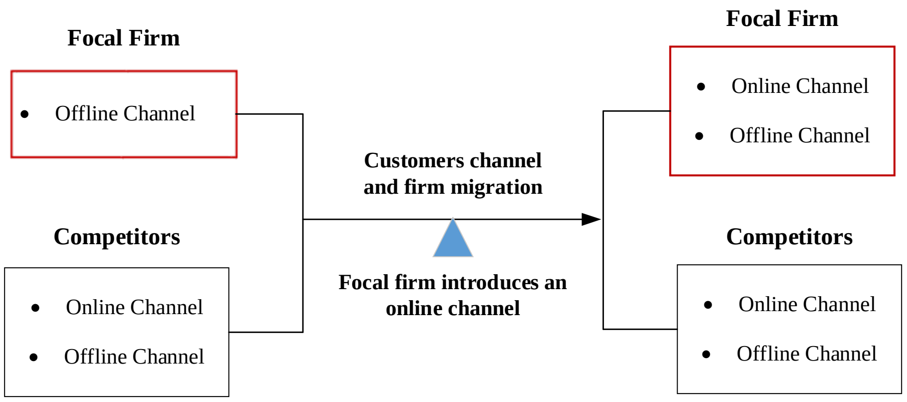

Figure 3.1: Customer Channel Migration in a Competitive Environment

The increasing competitiveness of multichannel environment also makes it vital to investigate the consequences of new channel introductions, especially the effects on competition among firms. Many studies argue that firms benefit from introducing online channels, through more revenues (Coelho et al. 2003; Gensler, Verhoef, et al. 2012; Xue et al. 2011), better stock market returns (Geyskens et al. 2002; Lee and Grewal 2004), increased customer retention (Boehm 2008; Campbell and Frei 2009), or greater customer loyalty (Shankar, Smith, and Rangaswamy 2003; Wallace et al. 2004). Other studies indicate instead that an online channel introduction increases average service costs (Campbell and Frei 2009), while diminishing customer purchase frequency (Ansari et al. 2008; Thomas and Sullivan 2005). In this debate, we find no indication of how customers' adoption of a new online channel affect their purchases from competitors. Yet a clear understanding of the effects of competition in multichannel marketing should provide a more accurate assessment of the value of adding a new channel to a retail assortment (Dholakia et al. 2010; Moe and Yang 2009; Neslin and Shankar 2009).

Against this background we investigate customer channel migration in the multichannel competitive environment by examining two research questions:

(1) *How do customers' previous purchases from competitors' online and offline channels affect channel migration of a focal firm's existing and new customers?*

(2) *How do customers' adoption and use of a new online channel affect their purchases from competitors and from the focal firm?*

To answer these questions, we model customer shopping behavior in a competitive multichannel environment according to purchase incidence, channel choice, and order size (Ansari et al. 2008). Although prior research notes that customers progress through several phases during the shopping process, such as information search, purchase, and after-sales (Neslin et al. 2006; Verhoef et al. 2007), we focus on actual shopping behavior during the purchase phase. In doing so, we construct a model based on a unique multichannel purchase data gathered from ten retailers competing in the same category (home décor). Each customer has a unique identity that is identical across all retailers, so we can track customer purchases from all firms in this category over time. The customer transaction data span 42 months before and 54 months after a focal firm introduced a new online channel. We recognize the focal firm as a late entrant, because six retailers in this category have already established online sales channels and the first online entry happened seven years prior to the online launch of the focal firm. All retailers operate direct sales channels (Internet, catalog and telephone). Therefore, this research does not consider the effects of brick-and-mortar stores and offline channels in this research refer to the catalog and telephone channels.

Next we derive our conceptual framework from prior literature pertaining to competition effects, channel choice, and channel introduction. After we present our hypotheses, we describe the study data and variables. Next we depict our methodology and report the results. Finally, in the conclusion, we summarize our key findings and discuss some managerial implications, limitations, and further research.

3.2. Conceptual Development

3.2.1 Literature Review

3.2.1.1. Effects of previous purchases from competitor's channels on current and future channel choice.

In marketing a pivotal question is how competitors' marketing activities affect customer shopping behavior and spending. To answer this question, many studies model the impacts of different types of marketing activities by competitors, such as promotion (Van Diepen et al. 2009; Nijs et al. 2001), advertising (Banerjee and Bandyopadhyay 2003; Prins and Verhoef 2007), new brand or product introductions (Van Heerde, Mela, and Manchanda 2004; Mahajan, Sharma, and Buzzell 1993), and new channel introductions (Brynjolfsson, Hu, and Rahman 2009; Forman, Ghose, and Goldfarb 2008; Moe and Yang 2009).

In a competitive environment, customers choose among multiple channels offered by different retailers, so apart from products and services, each firm confronts competition in marketing channels owned by other firms that sell similar products and services. A few studies investigate how customers choose among these multiple channels of competing firms. For example, Forman et al. (2008) empirically investigate the impacts of different factors on the choice between online and brick-and-mortar retailers, such as transportation costs, online disutility costs, pricing strategies, and store locations. They find that when a store opens locally, customers switch away from online channels. In a similar study, Brynjolfsson et al. (2009) investigate how geography and product categories affect customer demand for brick-and-mortar versus direct (online and catalog) retailers. Direct retailers face significant competition from brick-and-mortar retailers when they sell mainstream products, but they are nearly immune to competition when they sell niche products. Such studies focus on competition between single-channel retailers, or single- versus multichannel retailers; no study has investigated competition between multichannel retailers, such that the effects of competitors' multiple channels on channel migration of the focal firm remain unknown. According to Blattberg et al. (2008) and Neslin et al. (2006), previous channel usage and experience strongly determine customers' subsequent purchase and channel choices. Each channel used by customers creates specific value and contributes to overall channel preference and satisfaction (Montoya-Weiss et al. 2003), which influences customers' future channel selections (Ansari et al. 2008; Falk et al. 2007). Thus, we investigate the effects of customers' previous purchases from competitors on customer channel migration.

3.1.1.2. Effects of online channel introduction and adoption

An online channel introduction could generate positive consequences for firm performance, especially related to the customer profitability associated with customer revenue and costs to serve. First, online channels contribute to profitability by increasing customer revenues. Because customers who use the online channel perceive more information control (Ariely 2000) and enjoy greater convenience and accessibility (Brynjolfsson et al. 2003; Montoya-Weiss et al. 2003), online usage is associated with more transactions and higher customer revenues (Campbell and Frei 2009; Gensler, Leeflang, et al. 2012; Xue et al. 2011). Second, an online channel increases customer profitability by reducing the costs required to serve them. For example, Gensler et al. (2012) show that operating online banking decreases the costs to serve customers. Third, an online channel can support and complement other channels of the same firm. Therefore, the overall performance of a multichannel system is greater than the sum of the performance of each individual channel (Brynjolfsson et al. 2003)

However, other studies find (minimal) cannibalization between online and offline channels (Pauwels and Neslin 2015) and argue that online introductions increase average service cost (Campbell and Frei 2009). Ward

(2001) suggests that online shopping substitutes for catalog shopping more than for traditional brick-and-mortar retailing. In addition, online channels might increase free-riding, because the Internet offers minimal channel lock-in (Verhoef et al. 2007), so online shoppers can easily switch to other channels, including competitors' (Van Baal and Dach 2005). Finally, online channels might lower customer profitability by allowing for lower purchase frequency (Ansari et al. 2008; Thomas and Sullivan 2005).

Because the marketing actions of each firm in a category or industry affect all competitors (Van Diepen et al. 2009; Moe and Yang 2009), introducing an online channel may affect customer shopping behavior throughout that category. Prior research largely ignores the impact of online channel introductions on competition, possibly because of the difficulty of obtaining data that encompasses multichannel purchase records from both a focal firm and its competitors in the same industry. In response, we investigate the effects of customers' adoption and use of a newly introduced online channel on the purchases (purchase incidence and order size) achieved by both the focal firm and its competitors.

3.2.2. Conceptual Framework

Figure 3.2 shows the conceptual framework of this study. Following previous multichannel marketing research (Ansari et al. 2008; van Nierop et al. 2011), we assume that for each purchase, customers decide whether to purchase from the focal firm or competitors (purchase incidence), then determine which channel to use (channel choice) and consequently how much money to spend (order size). In doing so we extend the channel migration framework of Ansari et al. (2008) by including the effect of competition.

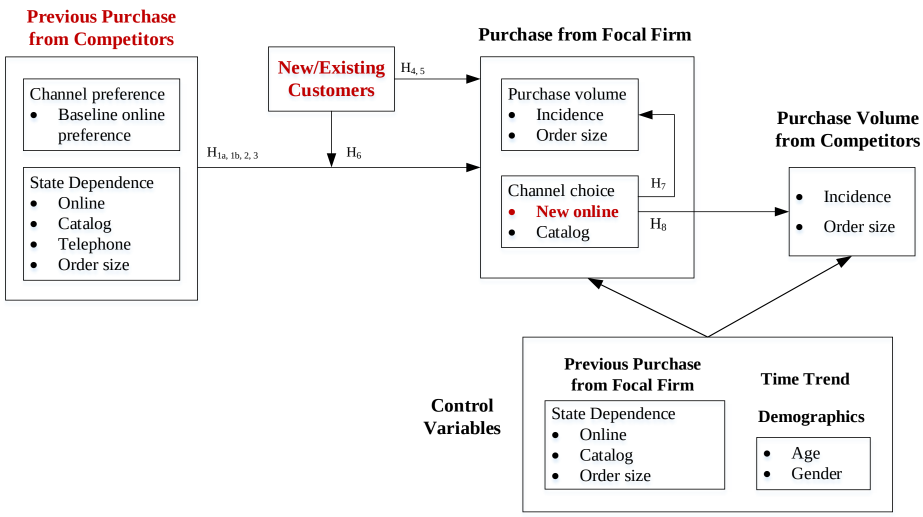

Figure 3.2: Conceptual Framework

Figure 3.2 considers the effects of customers' previous multichannel purchases from the focal firm and competitors, because customers' current purchase volumes and channel choice depend on their previous purchase experiences (Ansari et al. 2008; Konuş et al. 2014; Li et al. 2015). To accommodate our main research focus, our framework emphasizes the effects of online channel preference and state dependence of competitors on the channel choice (between online and catalog channel) of the focal firm and the influence of new online channel adoption on purchase volumes of competitors and the focal firm. We use customer channel preference together with state dependence to quantify customers' previous purchases. Following Konuş et al. (2014), customer channel preference refers to the customer's baseline percentage of purchases made through competitors' online channels prior to new online channel introduction by the focal firm. State dependence represents the customer's behavior status in the last month or last purchase occasion (Valentini et al. 2011), which reflects the inertial tendency to repeat recent decisions (e.g., channel choice or order size) but exert a shorter-term effect if compared to the impact of channel preference (Ailawadi, Gedenk, and Neslin 1999; Konuş et al. 2014). We distinguish between state dependence with the focal firm and with competitors.

We let the type of customer group (new and existing customers of the focal firm) moderate the effect of online channel preference with competitors and control for the effects of customers' previous purchases from the focal firm. Finally, we control for time effect (time trend) because channel choice processes and shopping behavior evolve over time (Ansari et al. 2008; Valentini et al. 2011) and demographics (incl. age and gender) that likely affect customer purchase incidence, channel choice, and order size (Inman et al. 2004; Shankar et al. 2003; Valentini et al. 2011).

3.2.3. Hypotheses

Following Figure 3.2 we formulate our hypotheses. We begin by discussing the effects of previous purchase from competitors' channels (incl. channel preference and state dependence) on customer current channel choice. Then, we explore the channel choice of existing and new customers, and the potential moderating effect of the customer group. Finally, we investigate the effects of online channel adoption and usage on purchase volumes with the focal firm and its competitors.

3.2.3.1. Effects of cross-channel competition on customer channel choice

Online channel preference with competitors. Existing research implies the coexistence of two possible rationales pertaining to the effect of online channel preference with competitors on customer channel choice. On the one hand, customers with high preference to competitors' online channels are likely to have more online shopping experience and obtain greater Internet knowledge, which could lead to an increased probability of purchasing from the new online channel of the focal firm. Researchers have found that Internet knowledge and previous online shopping experience eliminate the perception of the risk of online channel usage (Montoya-Weiss et al. 2003; Novak, Hoffman, and Peralta 1999), and thus enhance customers' trust in the new online channel introduce by the focal firm. Because the trust in online shopping is positively associated with online repurchase intention (Rose et al. 2012), we expect the preference to competitors' online channels to increase the chance of adopting the new online channel introduced by the focal firm in comparison to the chance of choosing the focal firm's catalog channel.

One the other hand, customers' previous shopping experiences of competitors' online channels, especially the positive experiences, could lead to a higher expectation of subsequent online shopping experiences (Weiner 2000), including the expectation of the new online channel introduced by the focal firm. Customer decision-making literature reveals that customers seek information and evaluate these information before their purchase decisions (Neslin et al. 2006; Puccinelli et al. 2009), such that customers browse the information of product, payment, delivery or return through a firm's website prior to purchase online. If the perceived quality (convenience) of these new online services is lower than customers' expectation, they are less likely to adopt the new online channel because of likelihood of dissatisfaction (Anderson and Sullivan 1993; Oliver 1980). Such disconfirmation (the gap between customers' expectation and perceived quality) is also likely to happen from the supply side. The services and shopping supports of a newly introduced online channel may be insufficient compared to established online channels provided by competitors and the existing catalog channel offered by the focal firm. Therefore, customers with high online preference with competitors may continue to purchase from competitors' online channels and choose the focal firm's existing catalog channel when they decide to switch from competitors to the focal firm.

Because we are uncertain which factor imposes the major influence, we propose two opposing hypotheses corresponding to the two arguments:

H_{1a}*: *Customers who have high online channel preferences with competitors are more likely to choose the focal firm's newly introduced online channel than its existing catalog channel.

H_{1b}*: *Customers who have high online channel preferences with competitors are more likely to choose the focal firm's existing catalog channel than its newly introduced online channel.

Channel state dependence with competitors. Customers' channel usage status in the last occasion (channel state dependence) strongly affects their subsequent purchases due to the effect of inertia (Konuş et al. 2014; Valentini et al. 2011). Previous studies reveal that customers are prone to purchase again from the same channel through which they have purchased recently (Ansari et al. 2008; Dholakia et al. 2005; Moe and Yang 2009). Therefore, when customers switch from competitors to the focal firm, they are likely to continue to purchase through the same channel through which they purchased with competitors in the previous month. Accordingly, we offer two hypotheses, referring to competitors' online and catalog channels:

H_2*: *Customers who purchased from competitors' online channels in the last occasion are more likely to choose the focal firm's newly introduced online channel.

H_3*: *Customers who purchased from competitors' catalog channels in the last occasion are more likely to choose the focal firm's existing catalog channel.

Existing and new customers. Channel choice may differ between the focal firm's existing customers and the new customers who are acquired after the online channel introduction, due to the effects of learning and selective customer response. Learning has a profound influence on the customer decision process. Customers learn from their previous experiences, evolving from a deliberative mind-set to an implemental mind-set (Gollwitzer and Bayer 1999). In line with this theory, Valentini et al. (2011) reveal that the channel decision process evolves over time; acquired customers become less responsive to marketing efforts and a significant learner segment becomes more driven by channel preferences over time. The catalog preference of a firm's existing customers should be well established before new online channel introduction, therefore these customers are less likely to respond to online marketing and are more likely to be driven by their catalog channel preference. Accordingly, we posit:

H_4: *Existing customers of the focal firm are more likely to purchase through the existing catalog channel than new customers acquired after the introduction of the online channel by the focal firm.*

On the other hand, new customers who are acquired after the event have not established strong channel preferences for the focal firm and may be more likely responsive to the firm's marketing communications that drive them to the online channel. Moreover, the new online channel acquires a group of new customers who had higher general online preferences before shopping from the focal firm. Avery et al. (2012) find that a newly introduced channel (store) brings in new customers at a faster speed than existing channels. The new customers acquired by the new online channel likely purchase continuously through this channel. Therefore, we hypothesize:

H_5: *New customers of the focal firm are more likely to purchase through the new online channel than existing customers.*

We now turn to hypothesize the moderating effect of above customer groups on the relationship between the online channel preference with competitors and channel choice. Compared to newly required customers, existing customers have a longer relationship and have purchased more times from the focal firm. Because relationship length and the frequency of interactions are positively associated with the trust between organizations and individuals (Becerra and Gupta 2003; Leisen and Hyman 2004), existing customers should have a higher level of trust in the focal firm than new customers. Increased trust leads to the reduction of uncertainty and perceived risk (Morgan and Hunt 1994), therefore existing customers of the focal firm are more likely to extend their preference and trust of competitors' online channels to the newly online channel offered by the focal firm. In contrast, new customers who have been acquired by the focal firm's existing catalog channel may lock in this recent established contact even with a higher online preference through purchasing from competitors, because they have not developed a full trust on the focal firm thus are more likely to perceive its new online channel as risky. Likewise new customers acquired through the new online channel may continue to purchase through the online channel, so their preferences to competitors' online channels have minor effects on their channel choice. In sum, we hypothesize:

H_6: *The online channel preference with competitors has a greater effect on the adoption and use of the new online channel by existing customers than by new customers.*

3.2.3.2. Effects of online channel adoption on customer purchases from the focal firm and from competitors

Following previous studies, we decompose customer purchases into purchase incidence and order size - the amount of a single purchase (Ansari et al. 2008; van Nierop et al. 2011; Pauwels and Neslin 2015). As the new customers who are acquired by the focal firm's new online channel are inevitably more likely to switch their purchases to the focal firm, we hypothesize the effects of online channel adoption only for the existing customers of a focal firm.

By adopting and using the online channel, customers are likely to enjoy a lower search cost, higher shopping convenience, and greater information control and availability (Ariely 2000; Brynjolfsson et al. 2003; Lynch and Ariely 2000; Xue et al. 2011). Although a few studies identify a negative relationship between online usage and purchase incidence (Ansari et al. 2008; Thomas and Sullivan 2005), more research evidence suggests that the adoption and use of an online channel should increase customer satisfaction and firm loyalty (Shankar et al. 2003; Wallace et al. 2004), thus enhance purchase incidence (Campbell and Frei 2009; Gensler, Leeflang, et al. 2012; Pauwels and Neslin 2015; Xue et al. 2011). Following previous research, we expect online channel adoption to increase purchase incidence of the focal firm for existing customers. Because customers often divide their purchases across several competing organizations (Dwyer 1997), existing customers are likely to reduce their purchases with competitors when they purchase more from the focal firm. Accordingly, we posit:

H_7: *Existing customers' adoption and use of the focal firm's newly introduced online channel increase their likelihood of purchasing from the focal firm.*

H_8: *Existing customers' adoption and use of the focal firm's newly introduced online channel reduces their likelihood of purchasing from competitors.*

Order size could relate negatively to purchase incidence; the economic order quantity model from operations management research indicates that it is preferable to achieve larger orders with lesser frequency if the cost per transaction increases (Taylor 2004). However, this assumption holds only if customer demand remains constant. As we discussed, adding a channel changes the focal firm's customer demand and market share, as well as the size of the overall market (Campbell and Frei 2009; Van Diepen et al. 2009; Gensler, Leeflang, et al. 2012). Previous research reveals that customers change their purchase incidence with a firm more than their order sizes in a multichannel environment. As Ansari et al.

(2008) note, marketing actions increase purchase incidence, not order size. Similarly, Pauwels and Neslin (2010) show that the addition of a channel increases revenue through purchase incidence with the focal firm, with no effect on order size. In addition, no empirical evidence describes the effects of online adoption on order sizes for competitors. We thus cannot have prior expectations on these effects and instead empirically explore them without formulating hypotheses.

3.3. Data and Variables

3.3.1 Data description

The data for this study came from a French multichannel database consultancy that collects longitudinal transactional data from multiple retailers, across multiple categories nationwide. We obtained customer transactional data from 10 multichannel retailers that compete in the home décor category, as we note in Table 3.1. These data spanned eight years, from January 2004 to December 2011. We selected one retailer as the focal firm, on the basis of three criteria. First, it introduced a new online channel in July 2007, so we could observe customers' shopping behavior before and after its introduction. Second, no retailers introduced any other new channels after this introduction, which eliminated the potential impact of the introduction of other firms' new channels on customer shopping behavior. Third, it was the third largest retailer in the panel, so we expect it to compete intensively with other retailers. To enable our analysis, we used the first 42 months, prior to the new online introduction (January 2004 to June 2007), to calculate loyalty variables in the baseline period. We employed the next 54 months, after the event (July 2007 to December 2011), to construct our models for the analysis period (Figure 3.3).

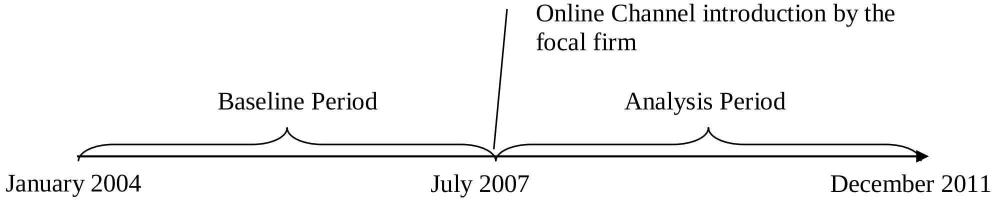

Figure 3.3: Timeline and Data Periods

Table 3.1: General Information about Retailers in the Sample

Retailer Identity	**Percentage of Transactions**	**Channel Owned**	**First Online Transaction Date**
Focal Firm	20.9%	Internet & catalog	September 2007
Competitor 1	34.6%	Internet, catalog, & telephone	May 2003
Competitor 2	26.1%	Internet, catalog, & telephone	September 2006
Competitor 3	6.9%	Catalog	
Competitor 4	5.5%	Internet & catalog	January 2000
Competitor 5	5.3%	Internet, catalog, & telephone	January 2005
Competitor 6	Less than 1%	Catalog	-
Competitor 7	Less than 1%	Catalog	-
Competitor 8	Less than 1%	Internet	September 2005
Competitor 9	Less than 1%	Internet & catalog	February 2007

To calculate customers’ channel and firm loyalties prior to the introduction of the new online channel, we included only those customers who had purchased at least once before the online introduction and customers who continued to purchase in this category after the online introduction. Otherwise we could not examine the effect of online adoption on customer purchase incidence and order size. With these selection rules we randomly chose a sample of 20,570 customers from the large data pool of 8,512,888 customers. All the retailers monitored customer purchases daily, though most customers do not shop that frequently in the home décor category. Table 3.2 contains the descriptive information of the selected sample. According to this table, customers purchase 1.12 times per year on average, with a maximum of 21.50 times per year in this category. Therefore, we aggregated purchase occasions, channel choice, and order size for each customer on a monthly basis.

Table 3.2: Descriptive Statistics for Selected Customers (*N*= 20,570)

Variable	**M**	**SD**	**Min**	**Max**
Purchases per year	1.12	0.96	0.25	21.50
Purchases over relationship	9.52	7.72	2	172
Average purchase (Euros)	78.25	136.70	0	11,587
Age	60.98	14.74	18	100
Gender (female)	94.85%			

Because this study focuses on the effects of competitors' channels on customer shopping behavior, we also aggregated data from nine competitive retailers. In these data, 22.13% of customers purchase from the focal firm and competitors, 9.79% purchase exclusively from the focal firm, and 68.08% only buy from competitors. Overall, the retailers in this category used three purchase channels: catalog, Internet, and telephone (see Table 3.1). The focal firm only had a catalog channel before it added its Internet channel, and 72.57% of its customers had adopted the online channel by the end of the data period. Among customers of competitors, 21.60% bought products through online and offline channels during our study period, 22.67% purchased using catalogs and telephone orders, 45.94% purchased solely from the catalog, 5.52% bought only online, and 4.27% exclusively bought from the telephone channel. In a few cases, customers purchased from multiple firms or multiple channels in the same month; 3.9% of customers purchased from both the focal firm and competitors in the same month, and 5.2% purchased both online and offline in the same month. We accommodate those cases in our modeling approach.

3.3.2. *Variable Operationalization*

We classified our variables into three groups: (1) non-time-variant variables from the baseline period data, before the online channel introduction; (2) time-variant variables from the analysis period, after the online channel introduction; and (3) customer demographic variables (age and gender). We computed the variables related to customers' firm and channel preference in the baseline period, and then determined those pertaining to state dependence from the analysis period. Table 3.3 contains the details of our operationalization.

Table 3.3: Variable Definitions

Variable	Definition
Baseline Period	
Customer group (existing/new customers)	=1, if the customer starts to purchase with the focal firm before the online introduction; =0 otherwise
Baseline online preferences with competitors	Purchases from competitors' online channels/overall purchases
Analysis Period	
Online adoption and usage	= Log(1 + number of online purchases from the focal firm in the last month)
Online state dependence from focal firm	= 1 if the customer purchased online from the focal firm in the last month; 0 otherwise
Catalog state dependence from focal firm	= 1 if the customer purchased on catalogs from the focal firm in the last month; 0 otherwise
Online state dependence from competitors	= 1 if the customer purchased online from competitors in the last month; 0 otherwise
Catalog state dependence from competitors	= 1 if the customer purchased on catalogs from competitors in the last month; 0 otherwise
Telephone state dependence from competitors	= 1 if the customer purchased on telephone from competitors in the last month; 0 otherwise
Last order size of focal firm	Order size of the previous purchase made from the focal firm
Last order size of competitors	Order size of the previous purchase made from competitors
Recency	Number of months since the customer made the previous purchase in the last month
Time trend	Square root of time period, t = 0, …, 53
Customer Demographics	
Age	Continuous variables
Gender	Dummy variable (0 = female; 1 = male)

Baseline period variables. We used two variables to identify customers' channel preference and purchase status in the baseline period – the period before the introduction of the online channel. For channel preference, we used a variable to capture the baseline level of online preference, which a customer may achieve by using competitors’ online channels. In addition, we used a dummy variable to distinguish between new and existing customer groups. New customers are those who started purchasing from the focal firm after the online introduction; existing customers initially purchased from this firm, prior to the online introduction.

Analysis period variables. Two variables, computed from the data pertaining to the analysis period – the period after the introduction of the online channel, captured customers’ past purchase status from different firms: the size of the last orders with the focal and competitor firms. Five variables serve to represent customers’ past channel usage status with different firms: online state dependence from the focal firm and from competitors; catalog state dependence from the focal firm and from competitors; and telephone state dependence from competitors. We also computed recency as the time elapsed since the last purchase. Recency, frequency, and monetary value variables (RFM) frequently appear in prior models to investigate customer responses to different marketing activities (Ansari et al. 2008; Van Diepen et al. 2009). For the online adoption and usage variable, we calculated the log value of (1 + online purchases to date), to capture both forgetting and learning effects due to customers’ use of an online channel introduced by the focal firm in the previous period (Ansari et al. 2008).

3.4. Methodology

To assess the three customer decisions - whether to purchase from the focal firm or competitors, and if purchase, through which channel to complete the order, and what amount to spend - we used three separate methods and measured purchase incidence, channel choice, and order size.

We employed a bivariate probit model to determine whether a customer purchases from the focal firm and/or competitors in a particular month. Unlike univariate probit, the bivariate probit model can accommodate a situation in which a customer purchases from the focal firm and competitors in the same month

(Greene 2007). The bivariate probit model with sample selection thus reveals which channel a customer uses, conditional on a purchase from the focal firm in a given month. We also considered the situation in which a customer might purchase through online and catalog channels in the same month. Finally, we designed two panel regression models with sample selection (in line with Tobit II specifications) to determine the average order size per transaction, conditional on a purchase from the focal firm or competitors, in a given month. Thus, our model equations are as follows:

Model 1: Firm choice

$P_{itm} =$ Purchase from firm m, if P^*_{itm}>0; 0, otherwise (Eq. 3.1)

$P^*_{itm} = \beta_{im} G_{itm} + \varepsilon_{itm}$ (Eq. 3.2)

where, m = 1 (focal firm), 2 (competitors)';

P^*_{itm} is the latent utility of customer i to purchase from firm m in month t.

Model 2: Channel choice

C_{itn} = Purchase on channel n from focal firm, if $C^*_{itn} > 0$ & $P^{\,*}_{it1} > 0$; 0, otherwise (Eq. 3.4)

$C^*_{itn} = \delta_{in} H_{itn} + \mu_{itn}$ (Eq. 3.5)

where, n = 1 (online), 2 (catalog);

C^*_{itn} is the latent utility of customer i to purchase on channel n from firm the focal firm in month t.

Model 3: Order size

$Q_{itm} = Q^*_{itm}$, if $P^*_{itm} > 0$; unobserved, if $P^*_{itm} \leq 0$ (Eq. 3.5)

$Q^*_{itm} = \theta_{im} K_{itm} + \tau_{itm}$ (Eq. 3.6)

where, Q^*_{itm} is the latent utility of order size from firm m in month t.

These three equations contain several explanatory variables in common, but some variables are unique to the specific equations. In Table 3.4 we consider the composition of the vectors G_{itm}, H_{itn}, and. K_{itm}. To enhance the integration of our models, we mean-centered all variables except for dummies (i.e., customer segment, state dependence, and gender) and create several interaction terms in the models.

Table 3.4: Variables of Purchase Incidence, Channel Choice, and Order Size Models

Variable	**Purchase Incidence**	**Channel Choice**	**Order Size**
<u>Baseline Period</u>			
Customer group (existing/new customers)	√	√	√
Baseline online preference with competitors		√	
<u>Analysis Period</u>			
Online adoption and usage	√		√
Online state dependence from focal firm	√	√	
Catalog state dependence from focal firm	√	√	
Online state dependence from competitors	√	√	
Catalog state dependence from competitors	√	√	
Telephone state dependence from competitors	√	√	
Last order size of focal firm			√
Last order size of competitors			√
Recency	√	√	√
Time trend	√	√	√
<u>Customer Demographics</u>			
Age	√	√	√
Gender	√	√	√
<u>Interactions</u>			
Baseline online preference with competitors × Customer group		√	
Online adoption × Customer group	√		√

3.5. Results

We checked the correlation matrixes of the three models (see Table 3.5 and 3.6). All correlations are less than .56 and the majority of them are less than 0.35, significant at the 0.001 level.

Table 3.5: Correlation Matrix: Purchase Incidence and Channel Choice Models

	Online adoption	Customer group	Baseline online preference	Online SDFF	Catalog SDFF	Online SDC	Catalog SDC	Telephone SDC	Recency	Time trend	Age	Gender
Online adoption	1											
Customer group	0.339	1										
Baseline online Preference	-0.038	-0.146	1									
Online SDFF	0.267	0.090	-0.008	1								
Catalog SDFF	0.120	0.217	-0.038	0.015	1							
Online SDCs	0.009	-0.026	0.167	0.008	-0.008	1						
Catalog SDCs	-0.025	-0.063	-0.058	-0.003	-0.005	-0.015	1					
Telephone SDCs	-0.012	-0.032	-0.015	-0.001	-0.002	0.006	0.009	1				
Recency	-0.170	-0.065	-0.027	-0.070	-0.124	-0.104	-0.204	-0.103	1			
Time trend	0.220	-0.000	0.000	0.032	0.018	0.026	0.029	-0.001	0.016	1		
Age	-0.050	-0.050	-0.341	-0.016	0.005	-0.105	0.080	-0.017	0.001	0.000	1	
Gender	-0.045	-0.0585	-0.029	-0.010	-0.018	-0.014	0.013	-0.010	0.035	0.000	0.066	1

Notes: SDFF = state dependence from focal firm; SDC = state dependence from competitors

Table 3.6: Correlation Matrix: Order Size Model

	Online adoption	Customer group	LOS of focal firm	LOS of competitors	Recency	Time trend	Age	Gender
Online adoption	1							
Customer group	0.339	1						
LOS of focal firm	0.287	0.558	1					
LOS of competitors	-0.090	-0.157	-0.157	1				
Recency	-0.170	-0.065	-0.037	-0.006	1			
Time trend	0.220	-0.000	0.010	-0.016	0.016	1		
Age	-0.050	-0.050	-0.026	-0.150	0.001	0.000	1	
Gender	-0.045	-0.059	-0.027	-0.011	0.035	0.000	0.066	1

Notes: LOS= Last order size

3.5.1. Results of channel choice model

Table 3.7 presents results of channel choice model. Online preference with competitors increased the probability that they would choose the newly introduced online channel (.003, $p < .001$), and it was negatively associated with the use of the focal firm's catalog channel (-.004, $p < .001$), in support of H_{1a} instead of H_{1b}. After the new online entry, online state dependence with competitors positively affected their likelihood of online adoption (.820, $p < .001$) and negatively affected catalog usage (-.788, $p < .001$), which supports H_2. These results suggest that customers' previous purchases with competitors' online channels increase the probability that a customer adopts and purchases from a new online channel. Surprisingly, catalog state dependence with competitors also increased the probability of choosing the new online channel (.370, $p < .001$) and diminished the likelihood of using the existing catalog channel (-.363, $p < .001$). Thus, we do not find support for H_3. Telephone state dependence with competitors had similar effects as catalog channels, although its effect on catalog selection is not significant.

Table 3.7: Results of Channel Choice Model (Focal Firm)

	Online		Catalog	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**
Constant	-0.643	0.000	0.691	0.000
Customer group (existing customer=1)	-0.316	0.000	0.319	0.000
Variables with Competition				
Baseline online preference with competitors	0.003	0.000	-0.004	0.000
Online state dependence from competitors	0.820	0.000	-0.788	0.000
Catalog state dependence from competitors	0.370	0.000	-0.363	0.000
Telephone state dependence from competitors	0.175	0.054	-0.113	0.212
Variables with the Focal Firm				
Online state dependence from focal firm	1.294	0.000	-1.231	0.000
Catalog state dependence from focal firm	-0.133	0.000	0.228	0.000
Control Variables				
Recency	0.046	0.000	-0.045	0.000
Time trend	0.074	0.000	-0.070	0.000
Age	-0.011	0.000	0.011	0.000
Gender	0.060	0.241	-0.067	0.191
Interactions				
Baseline online preference with competitors × Customer group	0.014	0.000	-0.013	0.000

Compared to new customers, existing customers were less likely to purchase from the new online channel (-.316, p < .001), and more likely to purchase on the existing catalog channel (.319, p <. 001), which support our expectation in H_4 and H_5 respectively. We discovered a positive interaction between baseline online preference with competitors and the customer group (.014, p < .001) in the Internet channel equation, with a corresponding negative interaction in the catalog channel equation (-.013, p < .001). The effect of online preference with competitors on channel choice thus was greater for existing than for new customers, suggesting supporting H_6.

With respect to the effects of the focal firm' channels and other control variables, online state dependence with the focal firm drive customers to purchase from the new online channel (1.294, $p < .001$), and catalog state dependence with the focal firm enhanced catalog purchases of the focal firm (.228, $p < .001$). Thus, different from the response to competitors' channels, customers do have the tendency to follow their channel status with the focal firm in the last purchase occasion. The time trend variable revealed positive impacts on the choice of the online channel (.074, $p < .01$) and negative effects on the choice of the catalog channel (-.070, $p < .001$). The two recency coefficients also suggested that with a long gap between purchases, customers were more likely to purchase online (.046, p < .001) and less likely to purchase through the catalog (-.045, p < .001). These results suggested that customers were migrating to the new online channel since the introduction of this channel. Age negatively affected online usage (-.011, $p < .001$) and positively affected catalog usage (.011, $p < .001$); gender did not affect channel choice for the focal firm.

3.5.2. Results of Purchase Incidence Model

We present the results of purchase incidence model with the focal firm and competitors in Table 3.8. As we expected, customers' adoption and use of the focal firm's newly introduced online channel increased new customers' purchase probability with the focal firm (1.456, $p < .001$) and reduced their purchases with competitors (-.136, $p < .001$). Online adoption and usage exerted less effects on the purchases of existing customers, however, these customers were also more likely to purchase from the focal firm (1.456-1.411=0.045, p < .001) and less likely to shop from competitors after adopting the new online channel (-.136+.062=-.74, p < .001), in support of H_7 and H_8 respectively.

Table 3.8: Results of Purchase Incidence Model

	Focal Firm		Competitors	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**
Constant	-2.625	0.000	-1.385	0.000
Online adoption and usage	1.456	0.000	-0.136	0.000
Customer group (existing customer=1)	1.265	0.000	-0.376	0.000
Variables with Competition				
Online state dependence from competitors	-0.122	0.000	0.306	0.000
Catalog state dependence from competitors	-0.035	0.026	0.287	0.000
Telephone state dependence from competitors	-0.118	0.000	0.301	0.000
Variables with the Focal Firm				
Online state dependence from focal firm	0.126	0.000	-0.029	0.255
Catalog state dependence from focal firm	0.307	0.000	-0.106	0.000
Control Variables				
Recency	-0.006	0.000	-0.008	0.000
Time trend	0.036	0.000	0.044	0.000
Age	0.002	0.000	0.001	0.000
Gender	-0.116	0.000	-0.024	0.002
Interactions				
Online adoption and usage × Customer group	-1.411	0.000	0.062	0.000

In intuitively appealing results, the effects of channel state dependence variables followed the rule: a purchase in the previous month (regardless of the channel used) increased the probability of another purchase from the same firm and reduced the likelihood of purchasing from competitors. Our results revealed significant, negative effects of recency on the purchase incidence for both the focal firm (-.006, $p < .001$) and competitors (-.008, $p < .001$), which may reflect a feature of the home décor category. On average, customers made only 1.12 purchases per year - relatively few compared with other industries (Ansari et al. 2008; Van Diepen et al. 2009). Because the average period between two purchases was so long, it might be difficult for customers to recall the particular firm or brand from which they bought previously, and their purchase patterns could be interrupted easily by their use of other firms or brands. Therefore, the longer the time since their last purchase, the less likely customers may be to purchase from the firm. Because the time trend variable positively influenced purchase incidence for the focal firm (.036, $p < .001$) and competitors (.044, $p < .001$), customers appeared more likely to purchase from both sides over time. Finally, age showed a positive effect on purchase incidence for the focal firm (.002, $p < .001$) and competitors (.001, $p < .001$), whereas gender exerted a negative impact on purchase incidence for the focal firm (-.116, $p < .001$) and competitors (-.024, $p < .001$). Thus, older women were more likely to purchase.

3.5.3. Results of Order Size Model

Table 3.9 shows the results of the order size model with the focal firm and competitors. For the order size of focal firm, the online adoption and usage variable had a strong positive effect on the average order size of new customers (102.526, $p < .001$), but reduced the average order size spent by existing customers (102.526-108.116 = -6.41, $p < .001$). With respect to the order size of competitors, the online channel adoption and usage increased the average order size of both new and existing customers (6.168, $p < .05$); the effect of customer group was not significant.

The firm state dependence variables - last order sizes for both the focal firm and competitors revealed significant, positive impacts on the resultant order sizes in both cases ($p < .001$). When a customer spends more on previous purchases (regardless of firm), he or she likely purchases more thereafter. Age positively influenced the order sizes of the focal firm (.164, $p < .1$) but reduced the order sizes of competitors (-1.204, $p < .001$). Female customers were more likely to purchase with larger order size from both the focal firm and competitors than the male ($p < .001$).

Table 3.9: Results of Order Size Model

	Focal Firm		Competitors	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**
Constant	-261.426	0.000	55.064	0.000
Online adoption and usage	102.526	0.000	6.168	0.016
Customer group (existing customer=1)	145.652	0.000	-1.018	0.773
Variables with Competitors				
Last order size of competitors	0.124	0.000	0.177	0.000
Variables with the Focal Firm				
Last order size of focal firm	0.291	0.000	0.194	0.000
Control Variables				
Recency	0.217	0.001	0.038	0.186
Time trend	4.147	0.000	0.243	0.510
Age	0.164	0.001	-1.204	0.000
Gender	-14.801	0.010	-5.716	0.000
Interactions				
Online adoption and usage × Customer group	-108.116	0.000	-2.566	0.468

We summarize our hypotheses and the related results in Table 3.10.

Table 3.10: Summary of Results for Hypothesis Testing

Hypothesis	**Results**
H_{1a}: Customers who have high online channel preferences with competitors are more likely to choose the focal firm's newly introduced online channel than its existing catalog channel.	Supported
H_{1b}: Customers who have high online channel preferences with competitors are more likely to choose the focal firm's existing catalog channel than its newly introduced online channel.	Not supported
H_2: Customers who purchased from competitors' online channels in the last occasion are more likely to choose the focal firm's newly introduced online channel.	Supported
H_3: Customers who purchased from competitors' catalog channels in the last occasion are more likely to choose the focal firm's existing catalog channel.	Not supported
H_4: Existing customers are more likely to purchase through the existing catalog channel than new customers acquired after the introduction of the online channel by the focal firm.	Supported
H_5: New customers are more likely to purchase through the new online channel than existing customers.	Supported
H_6: The preference to competitors' online channels has a greater effect on the adoption and use of the new online channel by existing customers than new customers.	Supported
H_7: Existing customers' adoption and use of the focal firm's newly introduced online channel increase their likelihood of purchasing from the focal firm.	Supported
H_8: Existing customers' adoption and use of the focal firm's newly introduced online channel reduces their likelihood of purchasing from competitors.	Supported

3.6. Discussion and Implications

3.6.1. Theoretical Implications

This study has investigated how the cross-channel effects of competitors' channels affect customer channel migration across firms and channels, as well as the effects of online channel adoption and use on purchase volumes with competitors and the focal firm. We discuss the theoretical implications of our findings.

Customer channel migration in the competitive environment. The existence of competitors' online channels is not always harmful for a late entrant to introduce its new online sales channel. Instead, customers' previous purchases from these online channels (incl. both online preference and online state dependence with competitors) promote their adoption and migration to the new online channel by the late entrant. These findings are new in the multichannel research, but are consistent with previous studies on competitive advertising. Competitive advertising that features similar products or services can accelerate innovation adoption or enhance sales, because it may increase the awareness and penetrating rates of new products or services (Krishnan, Bass, and Kumar 2000; Prins and Verhoef 2007). For example, Prins and Verhoef (2007) reveal that competitive mass advertising on service shortens customer adoption duration of new services, and Van Diepen et al. (2009) note that competitive direct mailings increase the revenues of the focal firm in a short term. Our research suggests the benefits of competitors' actions are also salient with respect to customer adoption of a new online channel. The customers who had previously shop from competitors' online channels are more likely to adopt, because they may have greater Internet knowledge and fewer risk concerns of shopping online.

However, customers do not always follow their past channel state dependence when switching from competitors to the focal firm. If a customer purchased from competitors' offline channels in the last month, he or she is more likely to choose the new online channel when purchasing with the focal firm. Therefore, customers may perceive the same channel differently from one firm to another. We propose two reasons that could explain the failure of inertial effect on customer behavior. First, customers make cautious decision when they switch from competitors to the focal firm. Literature on decision making reveals that a customer could follow an automatic cognitive process to repeat past behavior unconsciously, when the behavior is well leaned and happens in a constant environment (Aarts et al. 1998; Ouellette and Wood 1998; Wood, Quinn, and

Kashy 2002). Customers conduct deliberate decision making under a unstable or difficult context (Wood et al. 2002). Therefore, moving from competitors to the focal firm, customers are likely to re-evaluate the benefits or costs between online and offline channels, thus they may not repeat their previous behaviors. The study of Moe and Yang (2009) supports this argument and asserts that the short-term effect of inertia can be disrupted easily by a new competitive online entry. The second reason is related to the supply-side effect. Retailers that introduce new online channels may encourage or reward customers for shopping through its newly introduced online channel. Because customers follow cautious decision making processes when switch firms, they are more likely to consider and be affected by these external stimulations, thus choose the new online channel for shopping.

A firm's existing and new customers have varied channel choices and respond differently to competitor's online channels. Compared to new customers, the existing customers are more engaged with the established catalog channel which they are already shopping and less likely to purchase through the new online channel. This finding is consistent with existing literature, such that customers making more purchases or having a longer relationship with firms are more likely to stay in a firm's established sales channels instead of a newly introduced online channel (Gensler et al. 2007; Li et al. 2015; Valentini et al. 2011). Although existing customers likely lock in the existing catalog channel, their previous purchase experiences with competitors' online channels can greatly promote the chance to purchase from the new online channel. These results suggest firms considering different marketing strategies for the two groups of customers

Effects of online channel adoption on competition. Existing studies indicate that the benefits that firms could reap from online channel introduction decline as firms fall further behind in entering the market (Geyskens et al. 2002; Kalyanaram, Robinson, and Urban 1995). Geyskens et al. (2002) discover an inverted U-form relationship between the performance potential of online channel addition and entry order. Our research shows that even a rather late entrant can still benefit from online channel introduction. The effect of online channel is not limited in increasing customer purchases with the focal firm; it diminishes the purchases with competitors both for existing and newly acquired customers. Besides, the online channel adoption and usage greatly enhance the average order size of the focal firm spent by the new customers. However, our findings also reveal that existing customers reduce their order sizes slightly after the adoption of the online channel, and both new and existing customers could increase the order sizes from competitors after this action.

3.6.2. Managerial Implications

Our research offers several implications for practitioners who plan to introduce a new (online) channel but their actions are later than some of their competitors. First, managers should tailor their channel strategies to accommodate the special needs of new and existing customers. They may focus on stimulating the online purchases of new customers who are intrinsically more likely to purchase from the new online channel. Managers should be cautious on migrating new customers to the new online channel, because existing customers are much sticker to the existing catalog channel and may be unwilling to be forced to purchase through the new online channel. Therefore, managers may consider retaining the relationship with existing customers through the existing catalog channel, and migrate these customers gradually to the new online channel.

Second, managers should consider the effects of customers' previous purchases competitors' online and offline channels. Although existing customers have a higher preference to the existing catalog channel, their previous purchases from competitors' online channel greatly promote the chance of adopting the new online channel. Knowing customers' preferences toward competitors' channels (e.g., through surveys) could help managers better predict customers' responses to a newly introduced channel.

Third, managers should not hesitate to introduce their own online channels when competitors have already done so. Our study reveals a positive effect of online channel adoption on customer revenue in this condition, as well as a negative effect of online channel adoption on purchase frequencies with competitors. Although we focus on the Internet as a shopping channel, similar implications likely emerge for firms that launch other new online marketing channels (e.g., social networks) or mobile online channels (e.g., mobile web, mobile applications and iPad applications), which increasingly influence the ways customers interact with firms.

Last but not the least, this research also offers implications for firms that introduce online channels earlier than competitors. According to our findings, earlier entrants of online market voluntarily help their competitors by promoting the adoption of their new online channels. To prevent this, managers of earlier entrants should reward the loyalty for shopping through their online channels, for instance, by launching online loyalty programs or activities.

3.6.3. Limitations and Further Research

This study has several limitations that provide opportunities for ongoing research. First, limited by data availability, we investigated how cross-channel competition affects new online channel adoption and customer migration between Internet and catalog channels. With the proliferation of mobile technology and social media, firms increasingly introduce mobile applications and use social media to interact with their customers. Therefore, it is important to understand how the cross-channel competition affects customer adoption of mobile or other new channels, and customer channel migration, because each channel possesses unique features that might influence customer multichannel shopping behavior. Additional research thus should investigate customer migration across different channel combinations in the competitive environment.

Second, we uncovered an effect of cross-channel competition on customer buying. Additional research might explore its effects on customer searches for product information or use of after-sales services. A customer's shopping process consists of multiple shopping phases (Konuş et al. 2008; Neslin et al. 2006). Channel uses vary across these shopping phases, such that the use of a particular channel in one shopping phase does not guarantee its use at other times (Verhoef et al. 2007). For example, research shopping describes the propensity of customers to research a product in one channel, then purchase it in another, usually researching online and then purchasing in stores (Van Baal and Dach 2005; Konuş et al. 2008; Verhoef et al. 2007). Further research could extend this study by considering multiple phases of customer shopping process.

Third, we focused on the home decor category. Studies should replicate our findings in other industries or product categories to investigate their generalizability. Prior research has indicated that customers' channel migration and shopping behavior are affected by the industries and product categories in which they purchase; Ansari et al. (2008) find for example that Internet usage is negatively associated with long-term purchase incidence for durable products, whereas such usage raises the probability of purchase in the banking industry (Campbell and Frei 2009; Xue et al. 2011).

Finally, our data set did not contain information about marketing communications or attitudinal or psychographic data to identify customers' attitudes toward a particular channel or firm. Further research could include other covariates that might affect customer shopping behavior in the competitive multichannel environment or design panel surveys to enrich the available information about individual customers.

CHAPTER 4

How Do Instant Multi-Touchpoint Experiences Affect Customer Satisfaction and Behavior? A Real-Time Experience Tracking Approach[5]

Customers encounter and experience various touchpoints during their shopping trips with brands, i.e., traditional advertising, stores, online and word-of-mouth. The instant experience of each encounter establishes a customer's overall brand experience, and could influence customer attitude and subsequent behavior. However, conventional multichannel and customer experience research methods mostly suffer from a memory recall problem and the limited scope of investigated touchpoints, and are insufficient to trace the instant touchpoint experience. This study therefore applies a novel, real-time experience tracking method to address these limitations. An initial sample of 448 customers reported their touchpoint experiences via a mobile text message, every time they encountered the focal brand in a four-week period. With this data, we investigate (1) the effects of real-time multi-touchpoint experience on customer satisfaction, and (2) the instant impacts of multi-touchpoint experiences on customer behavior (i.e., transactions) over time, and (3) the different effects of the volume and valence measures of a touchpoint. Our results reveal that the effect of customers' touchpoint experiences on satisfaction mainly comes from the valences of touchpoints, and not from their volumes. Customers tend to continue previous shopping traits with a familiar brand, even shortly after having negative shopping experiences. Besides, the effects of touchpoint experience vary across touchpoint types and categories.

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[5] This chapter is based on a finished working paper as: Li, J., Konuş, U., Macdonald, E., Wilson, H. and Langerak, F.: How Do Multi-Touchpoint Experiences Affect Satisfaction and Behavior: A Real-Time Experience Tracking Approach Relationships.
Earlier version of this study have been presented at the 2014 Informs Marketing Science Conference (Atlanta, U.S.) and the 2015 EMAC conference (Leuven, Belgium).

4.1. Introduction

A notable phenomenon in the business world is the proliferation of touchpoints through which customers get access to products and services. For instance, a customer might become interested in a product after a recommendation from a friend or a good televised advertisement, then search for more information on the product's website before purchasing the product in stores. After using the product, the customer might talk to friends about the product or shopping experience, or post a review on a social network. The vast scope of potential touchpoints thus spans both contacts controlled by manufacturers or retailers and conversations generated by other customers.

Following Wilson et al. (2013, p.1), a touchpoint refers to "an encounter type", and an encounter is "a single episode of direct or indirect contact with the brand". Recent research emphasizes the holistic nature of customer experience that originates from all direct and indirect encounters or contracts with the brand throughout the whole customer shopping journey (Lemke et al. 2011; Meyer and Schwager 2007; Verhoef et al. 2009). Holistic customer experience thus implies two aspects. First, it involves the experiences with all touchpoints during a customer's shopping journey, including not only all marketing channels through which the customers interacts with firms for shopping (Neslin et al. 2006), but also those touchpoints largely involved in search and after-sales stages, such as one-way communications (e.g., mass, direct and in-store communications) exerted by firms, as well as word-of-mouth (WOM) and publicity in which neither the firm nor its channel partners are directly involved (Baxendale et al. 2015; Wilson et al. 2013). Second, the holistic customer experience contains the experiences of overall encounters associated with a touchpoint. As a customer experiences various encounters at different times during the shopping process, the formation of customer experience is a real-time and dynamic process. The instant feature of customer experience is also reflected in its influence on customer attitude and behavior. As revealed by attribution theory, customers assign causality to their experiences or events with firms, which determines future expectancy of satisfaction and thus influences subsequent behaviors (Heider 1958; Weiner 2000).

The multiplicity of media and channels indeed provides firms excellent opportunities to understand and influence customers' experiences and behaviors through a wider scope of touchpoints. However, this trend also enhances the complexity to trace the instant experiences with various types of touchpoints, and thus raises difficulties in understanding the effects of multi-touchpoint experiences on customer satisfaction and behavior. As a deeper understanding of customers' multi-touchpoint experiences can help firms allocate resources optimally across various marketing channels and media (Wilson et al. 2013), we investigate the effects of instant customer experiences of multiple touchpoints on customer satisfaction and behavior.

Customers' multi-touchpoint experiences play a critical role in shaping customer satisfaction and shopping behavior. Early studies identify satisfaction as a function of expectation, perceived quality, and disconfirmation (Anderson and Sullivan 1993; Fornell, Johnson, and Anderson 1996; Oliver 1980). In line with this theory many studies have investigated the direct impacts of the performance by a product attribute or encounter on customer satisfaction (Bolton and Drew 1991; Mittal, Ross, and Baldasare 1998; Smith, Bolton, and Wagner 1999). Some recent studies suggest that customer satisfaction might be shaped by the holistic experiences derived from the encounters between customers and brands (Lemke et al. 2011; Meyer and Schwager 2007; Verhoef et al. 2009). Yet, most empirical studies focus on a limited number of encounters and pertain mostly to the attributes of a product, service, employee response, or the physical surrounding (Bitner 1990; Van Doorn and Verhoef 2008; Maxham and Netemeyer 2002). In addition, research in multichannel domains investigates the effects of different types of touchpoints on customer shopping behavior and firm performance. Most studies consider the influence of limited types of touchpoints on customer shopping behavior (i.e., Ahluwalia et al. 2000; Assmus et al. 1984; Chevalier and Mayzlin 2006). A few studies explore the joint effects of mass media and WOM but at an aggregated level (i.e., Dewan and Ramaprasad 2014; Onishi and Manchanda 2012; Trusov et al. 2009).

These literature streams leave several important considerations insufficiently addressed. First, no studies trace the holistic customer experiences with brands during the whole shopping journey. Because every encounter could influence the customer's overall brand experience and affect customer behavior (Gentile et al. 2007; Meyer and Schwager 2007; Verhoef et al. 2009), it is important to capture the entire experience with multiple touchpoints in a single research framework and investigate their effects at an individual level. Second, no studies investigate customers' responses to their instant experiences with multiple touchpoints over time. The strength of these effects may vary across touchpoints, such that a customer might reject the offer just after a single negative experience, despite a wealth of positive encounters in the past through other touchpoints. Third, it is not clear how the volume and valence of various touchpoints affect customer behavior. The volume attribute reflects the frequency or amount of a touchpoint's encounters, and the valence attribute captures the instant emotion created by the experience through an encounter (i.e., positive and negative user ratings) (Duan et al. 2008; Liu 2006). Most studies focus on the volume effects of touchpoints (Assmus et al. 1984; Deighton et al. 1994; Dijkstra et al. 2005; Trusov et al. 2009). For those that consider the valence effect, they mostly investigate the influence of WOM or publicity valence (Ahluwalia et al. 2000; Liu 2006; Tirunillai and Tellis 2012). A better understanding of these effects might help firms determine the extent to which they should allocate their resources to increasing the quantity or quality of their touchpoints.

In response, we investigate the effects of holistic multi-touchpoint experiences on customer satisfaction and transaction (incl. product purchase and service usage) across different categories. Specifically, we address three research questions:

(1) *How do holistic customer experiences with multiple touchpoints affect customer satisfaction?*

(2) *How do the instant multi-touchpoint experiences affect online and offline behavior (i.e. transactions) over time?*

(3) *To what extent that do the volume and valence attributes of a touchpoint experiences differ with respect to their effects on customer satisfaction and behavior?*

To address these questions, we use a novel and mobile-based approach. We collect our data using a real-time experience tracking approach, as recently applied by some leading global organizations (Macdonald, Wilson, and Konuş 2012), but adopted by very few academic studies (Baines et al. 2011; Baxendale et al. 2015; Wilson et al. 2013). Customers send structured text messages every time they encounter the focal brand that is most frequently used in a category, and the messages contain specific information, including the type of touchpoint, the encountered brand, and the valence of the encounter that the customer experiences (Baines et al. 2011; Wilson et al. 2013). With this method, we can track individual and instant customer experiences across a wide range of touchpoints, unlike the limits imposed by transactional, media spending, or online clickstream data (Macdonald et al. 2012; Wilson et al. 2013). Furthermore, this method largely resolves the memory recall problem that hinders conventional survey methods (Macdonald et al. 2012; Wirtz et al. 2003).

We collect data pertaining to three categories (supermarket, banking, and healthcare) and track customers' touchpoint experiences and behaviors over a four-week period. Our initial data set consisted of 448 customers reporting more than 8,000 encounters across 10 touchpoints including the television, newspaper, billboard, direct communication, online banner, in-store communication, publicity, offline WOM, and online and offline transactions.

We make several contributions to the existing research. First of all, by investigating the effects of holistic multi-touchpoint experiences on customer satisfaction and behavior, we extend the coverage of touchpoints to include not just direct encounters between customers and companies but also indirect encounters initiated by other customers. Thus, this study can help firms identify the most influential touchpoints that should receive more marketing resources. Second, we investigate the effects of real-time touchpoint experiences on customer behavior over time and conduct this research at the individual level, which offers a more precise estimation of multi-touchpoint effect, compared to existing research. Third, we track customers' experiences with various touchpoints through a novel real-time experience tracking approach and extend the empirical application of this method. Fourth, we extend current research by incorporating the valence (instant emotional response) effect of every touchpoint that we investigate. Prior studies only investigate the valence of publicity and WOM. Last but not least, we explore the differences and similarities in the consequences of touchpoint experiences across various categories.

In the next section we present our conceptual framework, the theories that are relevant to our research, and propose hypotheses. After we describe data collection method and data characters, we present the modeling methods and our results. The findings reveal some theoretical and managerial implications, as well as limitations and suggestions for further research.

4.2. Conceptual Development

4.2.1. Touchpoint Typology and Conceptual Framework

To cover the various touchpoints that customers may experience during their shopping trips, we start by developing a framework of touchpoint classification.

Marketing communication research distinguishes between firm-initiated touchpoints (FITs) and customer-initiated contacts (CITs) (Bowman and Narayandas 2001; Wiesel et al. 2011). The FITs include any marketing communications or encounters with customers initiated by manufactures or retailers, such as paid mass advertisements, face-to-face and telephone communications, and e-mail campaigns. In contrast, CITs are encounters between firms and customers and are initiated by customers, such as purchases, searches, complaints, and inquiries (Bowman and Narayandas 2001; Li and Kannan 2013; Reinartz, Thomas, and Kumar 2005). Recent studies find CITs are more influential than FITs, such that their response rates and sales elasticity are much higher than those of traditional FITs (Sarner and Herschel. 2008; Wiesel et al. 2011). However, this classification ignores the encounters among customers (i.e., earned WOM and publicity), despite the potentially greater influence of these forms of encounters on customers' attitudes and shopping behavior (Ahluwalia et al. 2000; Van den Bulte and Lilien 2001; Duan et al. 2008). Therefore, we include these touchpoints into the touchpoint framework and use the term – other-initiated touchpoints (OITs) to represents the encounters that are related to companies' products and services, and are generated by customers or other publics.

Therefore, we make a distinction among three types of touchpoints: firm-initiated, customer-initiated, and other-initiated touchpoints. We apply this typology to classify the touchpoints that are investigated by this research (see Figure 4.1). In this research, FITs comprise the encounters (advertisements and promotions) through television & newspapers, billboards, online, and direct channels (incl. e-mails and post mails), as well as in stores such as in-store posters and product display on the shelf. CITs pertain to any encounters initiated by customers through the online or store channel, which differs across categories. Specifically, in supermarkets, the CIT entails product purchases or store visits, whereas for banking and healthcare, it involves service usage or information inquiries. Finally, OITs refer to offline WOM and publicity.

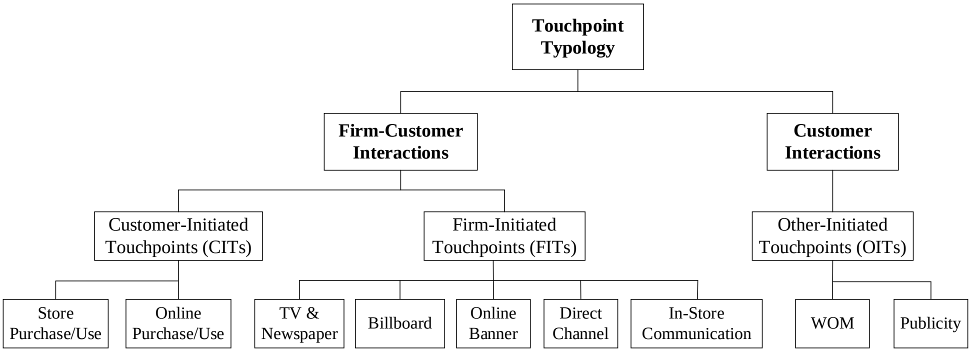

Figure 4.1: Touchpoint Classification Framework

Based on the touchpoint framework, we develop a conceptual framework in Figure 4.2 to investigate the effects of multi-touchpoint experiences with CITs, FITs and OITs on customer satisfaction and behavior over time. We build on the experience creation framework proposed by Verhoef et al. (2009) who propose that customer brand experience is created by all prior direct and/or indirect encounters with the companies during the whole shopping journey. In addition, to extend Verhoef et al.'s (2009) framework, we link customers' previous touchpoint experiences to satisfaction (top of Figure 4.2) and customer behavior (bottom of Figure 4.2). Customer behavior in our research refers to online and offline transaction (product purchase or service usage depending on category type), which is also the CITs. We detail the theories of each component and propose a set of hypotheses in the following sections.

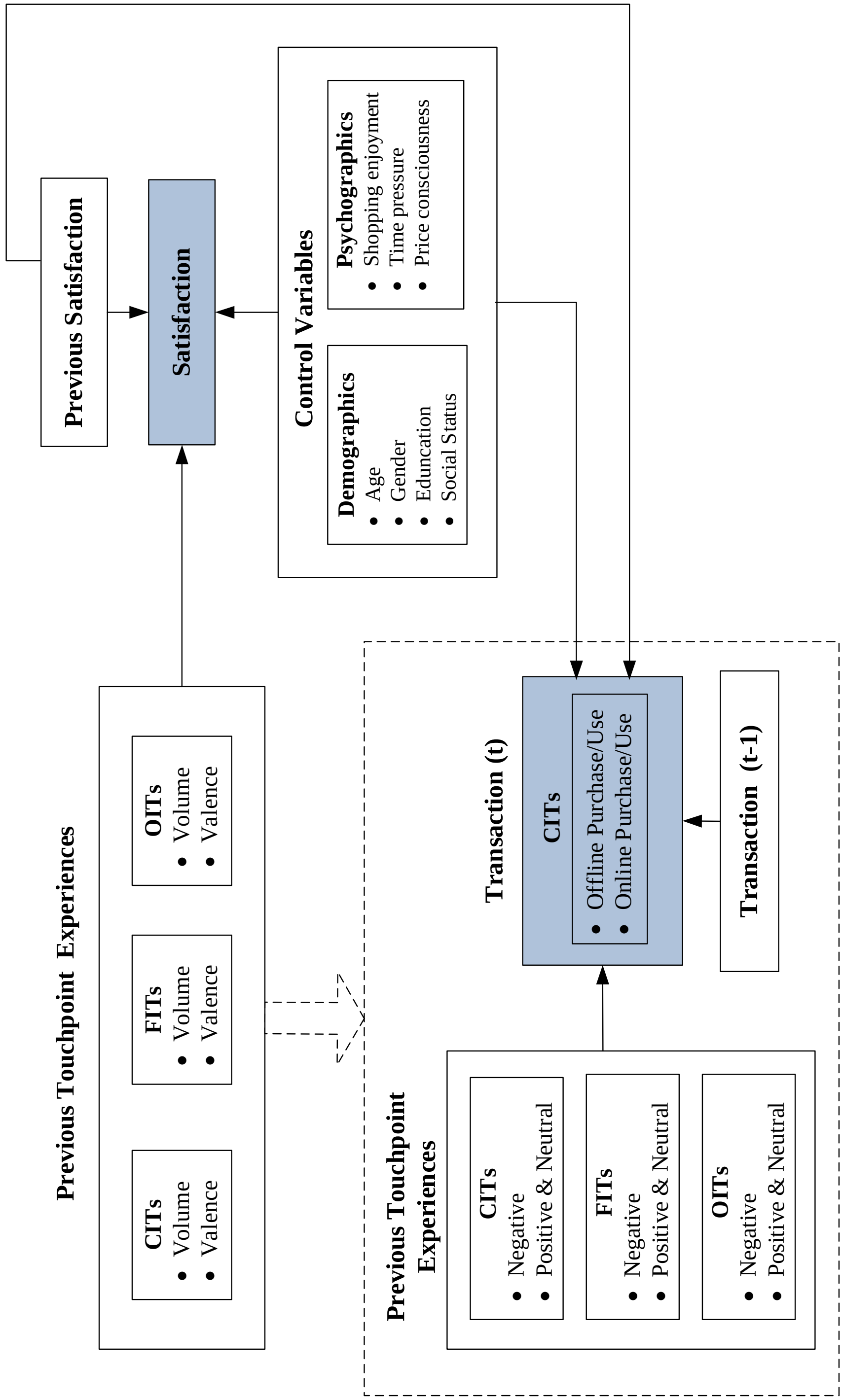

Figure 4.2: Conceptual Framework

4.2.2. *Effects of Multi-Touchpoint Experiences on Satisfaction*

Extensive research has sought to identify the antecedents of customer satisfaction (Anderson and Sullivan 1993; Fornell et al. 1996; Oliver 1980). To formulate our expectation with respect to the effects of multi-touchpoint experiences on satisfaction, we adopt the view of customer satisfaction as a function of expectation, perceived quality, and perceived value that is the perceived quality relative to the price paid (Anderson, Fornell, and Lehmann 1994; Fornell et al. 1996; Voss, Parasuraman, and Grewal 1998). We choose this model because it links a firm's market offerings (contacts, service, product, price, advertising spending) with satisfaction measures (Fornell et al. 1996).

We distinguish between a touchpoint' volume (frequency) and valence (instant emotional response created by customer's experience) that both impact satisfaction. The valence of a touchpoint can increase customer satisfaction although this relationship may be non-linear (Anderson and Sullivan 1993; Oliver and DeSarbo 1988). For example, many studies identify an asymmetric effect of disconfirmation on customer satisfaction, such that negative performance has a greater influence on satisfaction than positive performance (Anderson and Sullivan 1993; Bowman and Narayandas 2001; Mittal et al. 1998). Touchpoint volume also can determine customer satisfaction, such that multiple service failures lead to lower satisfaction than a single failure (Van Doorn and Verhoef 2008; Maxham and Netemeyer 2002). Most extant studies suggest that touchpoint valence plays the largest role in determining customer satisfaction though (Anderson and Sullivan 1993; Fornell et al. 1996; Oliver 1980). So we expect that the valence of a touchpoint exerts a greater influence on customer satisfaction than its volume. Due to the greater effect of touchpoint valence, we focus on this attribute and formulate our expectations with respect to the valence effects of CITs, FITs, and OITs on satisfaction.

Impact of CIT valence on satisfaction. Customers initiate encounters with firms to purchase products, use services, search for information, make inquiries, and complain. The overall experiences resulting from such encounters formulate customers' perceptions of product or service quality, and thus their judgments about the overall excellence or superiority of a product or service (Anderson et al. 1994; Bitner 1990; Maxham and Netemeyer 2002). Because the level of perceived quality has a strong and positive effect on customer satisfaction (Anderson et al. 1994; Mittal et al. 1998; Oliver and DeSarbo 1988), we hypothesize:

***H_{1a}*:** *CIT valence increases customer satisfaction.*

Impact of FIT valence on satisfaction. Customer satisfaction is also influenced by the perceived value, which is the perceived quality relative to the price paid, such that increased price elasticity lowers customer satisfaction (Anderson et al. 1994; Fornell et al. 1996). We predict that FITs influence customer satisfaction through their impact on perceived value and price elasticity. Previous studies note two types of information provided by FITs: (1) about brand attributes to help differentiate brands and influence brand preference, and (2) about brand name or image to increase brand awareness and influence the consideration set (Grewal, Chandrashekaran, and Citrin 2010; Mela, Gupta, and Lehmann 1997). Mitra and Lynch (1995) find that differentiating advertising can reduce price elasticity by increasing the relative strength of brand preference, whereas reminder advertising increases it by expanding the size of consideration set. Therefore, if a FIT contained information helping differentiate a brand from its competitors, the increased valence of this FIT should strengthen the differentiation effect and customers' preference to the focal brand over other brands in the same category, which should lead to lower price elasticity and greater satisfaction. However, if the FIT serves as reminders, its valence may not affect satisfaction, as customers' brand recall or awareness are mostly strengthened by message repetition, no matter whether the messages are positive or not (Briggs, Krishnan, and Borin 2005). Therefore, we posit:

H_{1b}*: *FIT valence increases customer satisfaction, only if the FIT contains information that promotes brand differentiation.

Impact of OIT valence on satisfaction. Banerjee (1992,1993) reveal that people are influenced by others' opinions thus alter their expectations of a brand's ability to deliver quality in the future. Similarly, Liu (2006) find positive WOM and publicity enhance expected quality, whereas their negative encounters reduce it. Therefore, the valence of OIT (WOM and publicity) should be positively associate with customer's expectation of the quality of a firm's outputs. Because the customer expectation increases the level of customer satisfaction (Anderson et al. 1994; Fornell et al. 1996), we propose:

H_{1c}*: *OIT valence increases customer satisfaction.

4.2.3. Effects of Multi-Touchpoint Experience on Customer Behavior

We also explore the influence of instant experiences with multiple touchpoints on customer online and offline transaction – customer-initiated touchpoints. We summarize relevant literature in Table 4.1, though we exclude studies that explore the outcomes of a single type of FIT and OIT. Rather, more relevant studies empirically explore the effectiveness of touchpoints across FITs and OITs. Many studies investigate the effects of OIT (e.g., online WOM) volumes on sales, innovation adoption, and other marketing performance measures (Van den Bulte and Lilien 2001; Chevalier and Mayzlin 2006; Dewan and Ramaprasad 2014; Duan et al. 2008; Godes and Mayzlin 2004; Stephen and Galak 2012). Recent research also notes their joint effects with FITs (Dewan and Ramaprasad 2014;

Onishi and Manchanda 2012; Stephen and Galak 2012; Trusov et al. 2009). For example, Trusov et al. (2009) and Pauwels et al. (2013) compare online WOM with other touchpoints and find that it may have a greater effect on customer actions (i.e., website sign-ups, store traffic) than FITs or publicity. Other studies examine the impacts of FIT and OIT volumes on customer behavior across sequential new product launch stages (Bruce, Foutz, and Kolsarici 2012; Gopinath, Chintagunta, and Venkataraman 2013; Onishi and Manchanda 2012). According to Bruce et al. (2012), the effect of paid advertising spending on sales is more influential in earlier stages, whereas online WOM activities become more powerful in driving customer demand later. Onishi and Manchanda (2012) also reveal that pre-launch television advertising spurs blogging (online WOM) activity, but this effect weakens during the post-launch period.

Despite the growing number of studies in this research area, most existing studies examine the performance of multiple touchpoints using an aggregated level that is sensitive to external factors and thus might lead to inaccurate estimations (Chintagunta, Gopinath, and Venkataraman 2010). Furthermore, although many studies identify an important effect of touchpoint valence on customer behavior, existing literature focuses on the valence effect of OITs (e.g., WOM and publicity) (Ahluwalia et al. 2000; Chevalier and Mayzlin 2006; Tirunillai and Tellis 2012). It is still unknown how customers' previous experiences with FIT and transactions affect current transaction. Therefore, we investigate the effects of individuals' previous experiences with FIT, OIT, and transaction on current transactions over time. Because negative information likely exerts more influence than positive information (Ahluwalia et al. 2000; Chevalier and Mayzlin 2006; Klein 1996), we separate each touchpoint's negative encounters from its positive and neutral ones to consider its valence effect.

Table 4.1: Overview of Relevant Literature from Multichannel and Multimedia Research

Study	Examined factor(s)	Firm-initiated touchpoints	Other initiated touchpoints	Valence/ Content	Individual/ Aggregate	Category
Trusov, Bucklin, & Pauwels (2009)	New sign-ups on website	Promotion event	Publicity, Online WOM	N	Aggregate	SNS provider
Yamamoto & Matsumura (2011)	Customer acquisition, online and offline WOM	TV	Online and offline WOM	N	Aggregate	Mobile SNS provider
Bruce, Foutz, & Kolsarici (2012)	Sales, online WOM	television, newspapers, and online	Online WOM	Valence of online WOM	Aggregate	Movie
Stephen & Galak (2012)	Sales, online WOM	Portal website	Traditional publicity, online WOM	N	Aggregate	Microlending
Onishi & Manchanda (2012)	Sales, online WOM	TV	Online WOM	Valence of online WOM	Aggregate	Movie, telecommunication
Bollinger, Cohen, & Jiang (2013)	Purchase and online WOM	TV, online banner, social network	Online WOM	Valence of online WOM	Individual	Consumer package goods
Gopinath, Chintagunta, & Venkataraman, 2013)	Sales	Traditional advertising spending	Online WOM	Valence of online WOM	Aggregate	Movie
Kim & Hanssens (2013)	Sales	TV, print, radio, and outdoor expenditure	Online WOM	N	Aggregate	Movie
Pauwels, Stacey, & Lackman (2013)	Online and store traffic, online WOM	TV, radio, print, online display	Online WOM	Content of online WOM	Aggregate	Retailing
Dewan & Ramaprasad (2014)	Sales, online WOM	Radio	Online WOM	N	Aggregate	Music industry
This research	Purchase, service usage, offline WOM, satisfaction	TV, print, billboard, direct channels, online banner, In store advertising	Traditional publicity and offline WOM	Valence of touchpoints	Individual	Product and Service

Impact of previous transaction (CIT) experiences on current transaction. People tend to continue their past behavioral traits unconsciously, because the multiple repetition of the same behavior formulates the habit that drives a person to remain the current status-quo (Aarts et al. 1998; Wood et al. 2002). Many studies have elaborated on this concept to explain a variety of persisting behaviors such as travel mode choice, service usage and shopping behavior (Limayem et al. 2007; Ouellette and Wood 1998; Shah et al. 2012). In the context of our research, the frequent repetition of positive transaction experiences likely strengthens the habitual effect (Aarts et al. 1998), thus increases the chance of persisting the same behavior (transaction) in the next occasion. Thus, we hypothesize:

H_2: *Positive instant experiences with previous transactions (CITs) increase the frequency of current transactions.*

Negative experiences with previous transactions may lead to two opposing effects on subsequent transactions. On the one hand, these negative transaction experiences could strengthen the habitual effect through the repetition of the same action. On the other hand, the negative experiences with previous transactions could invoke a negative evaluation or expectation of the sequent behavioral performance, which weakens the link between goal and behavior and reduces the probability of continuing this behavior (Aarts et al. 1998; Orbell et al. 2001). Because we are not clear which factor imposes the major influence, we propose two opposing hypotheses:

H_{3a}: *Negative instant experiences with previous transactions (CITs) increase the frequency of current transactions.*

H_{3b}: *Negative instant experiences with previous transactions (CITs) reduce the frequency of current transactions.*

Impact of previous FIT experiences on current transaction. The effects of firm-initiated touchpoints, especially paid adverting, promotion and sponsorship, on customer shopping behavior and firm performance have received ample attention (for a review, see Tellis and Ambler 2007). Extensive studies show that the effects of FIT on shopping behavior vary across markets and product categories, but are significantly greater than zero in most cases (Assmus et al. 1984; Deighton et al. 1994; Dijkstra et al. 2005). Based on the theory of message repetition, Tellis, Chandy and Thaivanich (2000) summarize the impact of advertising according to its three main effects: a current or instantaneous effect on brand referrals, a carryover effect on behavior, and a nonbehavioral effect on attitude and memory or brand recall. Following their theory, the positive and instant experiences with FITs could stimulate a customer's immediate response to these messages, formulate the positive attitude towards this brand, and increase brand awareness, thus promote the frequency of current shopping behavior. On the other hand, customers may evaluate their experiences with FITs as negative, when the contained messages are not attractive or not relevant to their shopping purposes. Although the negative experiences with FITs may not promote a customer's evaluation of the brand, they can still help customers recall brand name through the repetition thus enhance the brand awareness which is positively associated with purchase intentions (Briggs et al. 2005). Therefore, we hypothesize:

H_4: *Both positive and negative instant experiences with previous FITs increase the frequency of current transactions.*

Impact of previous OIT experiences on current transaction. Recent research on online WOM activities suggests that the volume of WOM increases purchase and service usage (Liu 2006; Stephen and Galak 2012; Trusov et al. 2009), yet extensive studies reveal that the valence of the messages delivered by customers or professional journalists also impact customer attitude and shopping behavior. This research area generally reveals that only positive WOM and publicity can promote customer purchases, whereas negative WOM or bad news harm product evaluations and reduce purchase likelihood or sales (Chevalier and Mayzlin 2006; Goldenberg et al. 2007; Huang and Chen 2006; Rui, Liu, and Whinston 2013; Tybout, Calder, and Sternthal 1981). Few studies identify an insignificant or even positive effect of negative publicity on customer attitude and purchase, but only within a specific context, e.g., for customers with high commitment (Ahluwalia et al. 2000) or unknown products (Berger, Sorensen, and Rasmussen 2010). Nevertheless we follow the general assumption and posit:

H_5: *Positive instant experiences with previous OITs increase the frequency of current transactions.*

H_6: *Negative instant experiences with previous OITs reduce the frequency of current transactions.*

2.2.4 Control Variables

We control for the carryover effect of previous satisfaction on current satisfaction, and its potential impact on subsequent behaviors, as suggested by previous studies (Van Doorn and Verhoef 2008; Mittal et al. 1998; Verhoef et al. 2009). Because customers are inertial to their behavioral status in the last occasion (Deighton et al. 1994; Valentini et al. 2011), we control for the effects of transaction status in the previous time period.

We also consider the influence of demographics and psychographics. Demographics have been extensively examined as the drivers of satisfaction (Dubé and Morgan 1996; Oliver and DeSarbo 1988), purchases and service usage (Cooil et al. 2007; Mittal and Kamakura 2001), channel choice (Ansari et al. 2008), and WOM generation (Yang et al. 2012). Thus, we include four commonly accepted demographical controls: age, gender, education, and social status. In addition, previous studies reveal that customers' psychographics can affect their shopping behavior and attitudes (Konuş et al. 2008; Verhoef et al. 2007; Wilson et al. 2013). Therefore we also control for the effects of shopping enjoyment, time pressure and price consciousness.

4.3. Data Collection and Description

4.3.1. Real-Time Experience Tracking Approach

We employed a real-time experience tracking approach to collect data related to three categories in the United Kingdom: supermarkets, banking, and healthcare. As we detailed in Figure 4.3, the data collection approach consisted of three components: (1) pre-study survey, (2) real-time experience tracking (main phase), and (3) post-study survey.

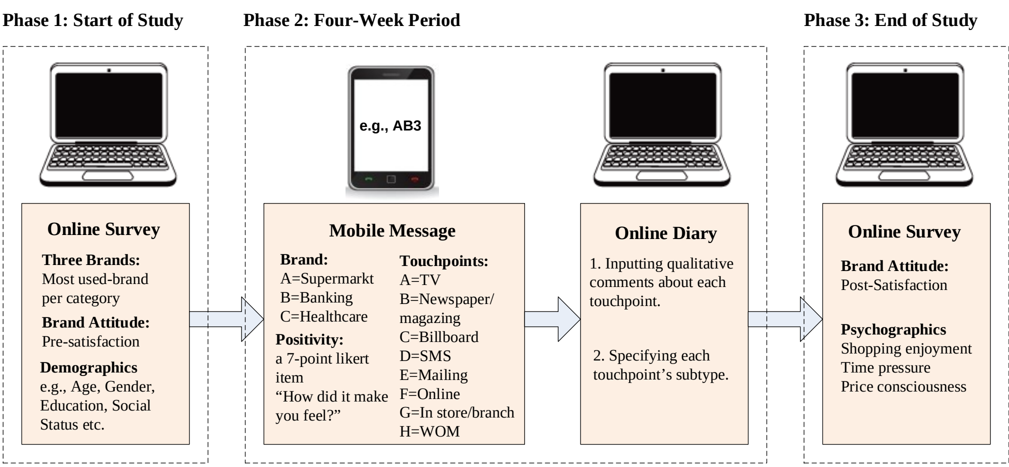

Figure 4.3: Data Collection Process

Pre-study survey. At the start of the study, each respondent completed a pre-study online survey, in which they selected their most frequently used brand from each category. They would then report only on encounters with that selected brand in the real-time tracking period. With this approach, we can collect a richer sample of brand encounters in the four-week survey period and ensure that the sample only contains a brand's existing customers (Wilson et al. 2013). This step also enhances the accuracy of the encounter reporting, because respondents only need to remember three brands and are less likely to confuse them with other brands in the same category. However, this sampling approach also excludes customers with low shares of brand wallet. In this survey respondents also needed to provide their satisfaction with the selected brand and give demographic information (i.e., age, gender, education, social-economic status, marital status, and occupation).

Real-time experience tracking (main phase). In a four-week period, respondents were required to send mobile text messages every time they encountered their three selected brands. The text message consisted of three characters: (1) a letter identifying the category, (2) a letter indicating the type of touchpoint, and (3) a number reflecting the customer's evaluation of the encounter. Figure 4.3 details these components. The system automatically captured the date and time of each message. Although the survey design was not limited to the eight touchpoints listed in Figure 4.3, we excluded touchpoints such as call centers, cinema advertisements and radio because they were rarely present in our dataset. In addition, respondents could provide qualitative comments with an online diary system, which offered valuable information about their subjective feelings about a specific encounter. This online diary also allows respondents to specify subtypes for each encountered touchpoint, such as whether an online encounter was a visit or transaction, a banner advertisement, or an e-mail received by the customer, as well as whether WOM was initiated by the respondent or by another person. We used this information to reframe the touchpoint types according to the classification in our framework.

Post-study survey. At the end of the real-time tracking period, respondents filled out a second online questionnaire that evaluated their current satisfaction with the brand and that also contained a set of psychographic characters, including shopping enjoyment, time pressure, and price consciousness. The gap between the pre-tracking and the post-tracking satisfaction enables us to determine how customer satisfaction changed due to customers' encounters with the brand over the previous four-week period (Macdonald et al. 2012).

4.3.2. Data Description

We conducted the study in February 2011. In total 448 customers participated and received a monetary token in return. No fees were charged per text message. Not every respondent reported encounters from all three categories during the four-week period. For each category, we included only those respondents who sent messages on at least two different days, because we aim to investigate the effects of touchpoint experiences on behaviors over time. Thus, the effective sample was 409 participants in the supermarket category, 349 in the banking category, and 213 in the healthcare category. In Table 4.2 we present the sample characteristics and in Table 4.3 we provide the encounter information across categories. In line with the category features respondents reported more encounters in the supermarket category (10.8 times per customer) than in the banking (7.7 times per customer) or healthcare (5.5 times per customer) categories.

Table 4.2: Summary of Sample Demographics (*N*=448)

Age	Mean	Min.	Max.
	41	18	64
Education			**%**
High (College/ university and above)			49.55
Low (High school and lower)			50.45
Marital Status			**%**
Married/ Partnership			72.10
Divorced/ Widowed			6.92
Single			20.98
Gender			**%**
Male			35.27
Female			64.73
Socio-Economic Status			**%**
High social class (ABC1)			74.55
Low social class (C2DE)			25.45
Occupation			**%**
Employed (paid, self-employed) full time			54.24
Employed (paid, self-employed) part time			22.10
Unemployed (retired, student, housewife)			23.66

Table 4.3: Summary of Encounters across Categories

Category	Total Number	Frequency per Customer	Standard Deviation	Min.	Max.
Supermarket	4,398	10.8	13.6	2	180
Bank	2,686	7.7	8.1	2	76
Health care	1,182	5.5	6.1	2	40

Table 4.4: Volume and Valence of Touchpoints across Categories

Touchpoint	Supermarket		Bank		Healthcare	
	Volume	Valence	Volume	Valence	Volume	Valence
Customer-initiated touchpoint (CIT)						
Store purchase/use	1,603	5.43	359	5.33	328	5.59
Online purchase/use	-	-	724	5.53	-	-
Firm-initiated touchpoint (FIT)						
TV & newspaper (indoor)	1,676	5.32	808	5.01	55	5.05
Billboard (outdoor)	183	5.34	164	5.1	74	5.47
Direct communication	314	5.47	271	4.76	86	5.62
Online banner	103	5.31	99	4.80	-	-
In-store communication	282	5.55	44	4.73	41	5.85
Other-initiated touchpoint (OIT)						
Publicity	112	4.33	143	3.65	450	3.46
Word-of-mouth (from other persons)	61	5.38	33	3.82	80	4.13
Word-of-mouth (to other persons)	64	4.31	41	4.85	68	4.41
Total number	4,398		2,686		1,182	

On the basis of our touchpoint framework, we reframed the encounters into nine types and three sub-categories (FIT, CIT and OIT), with their volumes in Table 4.4. Not every category has ten touchpoints though. For example, no online transaction touchpoints applied in the supermarket category, and we excluded online transaction and online banner encounters from the healthcare category, because customers rarely reported or encounter such touchpoints in these categories. To simplify the models and increase touchpoint volumes, we merged touchpoints that shared similar features, such that we combined SMS and e-mail encounters into a direct communication touchpoint, and television and newspapers into an indoor communication touchpoint, representing encounters that customers receive at home. We distinguished the offline word-of-mouth that a customer received from other persons from those that were sent by the customer.

Although online WOM is an important driver of customer behavior, its volume and ratios are extremely low (less than 10 times or .1%) in all three categories. Thus, we chose not to include online WOM in our framework. Publicity referred to news, articles, or blogs published by newspapers, magazines, television, and online.

4.4. Methodology

4.4.1. Measures

We measured customer satisfaction (pre-tracking and post-tracking satisfaction) and psychographic characters with a series of multi-item, seven-point Likert scales (1 = “strongly disagree” to 7 = “strongly agree”) that we derived from extant studies (summarized in Table C.1 in Appendix C). For customer satisfaction, we combined a three-item scale from De Wulf, Odekerken-Schröder, and Iacobucci (2001) and a one-item scale by Dubé and Morgan (1996). We adopted two of Konuş et al.'s (2008) two-item scales to measure shopping enjoyment and time pressure. For price consciousness, we integrated the two-item scale of Konuş et al. (2008) with a one-item scale adapted from Lichtenstein, Netemeyer, and Burton (1990). The properties of the scales were examined using principle component analysis (PCA) with a varimax orthogonal rotation for each category. Detailed results are reported in Appendix C (Table C.2 and C.3), and Table 4.5 presents the loading of each item. The eigenvalues of all factors were greater than 1 and the majority of the factor loadings were greater than .8, thus meeting the recommended thresholds (Hair et al. 2010). We assessed the reliability of the scale items using Cronbach’s alpha (Diamantopoulos and Winklhofer 2001). As shown in Table 4.5 the reliability coefficients are all greater than .7 (Ferrer, Hamagami, and McArdle 2004). In view of this, we averaged the scale items to represent the corresponding variable.

Table 4.5: Summary of Satisfaction and Psychographics

	Supermarket		Banking		Healthcare	
	Loading	Cronbach alpha	Loading	Cronbach alpha	Loading	Cronbach alpha
Post-satisfaction						
Item 1	0.875	0.932	0.939	0.959	0.913	0.954
Item 2	0.899		0.932		0.942	
Item 3	0.926		0.949		0.948	
Item 4	0.914		0.948		0.943	
Shopping enjoyment		0.826		0.826		0.826
Item 1	0.897		0.898		0.900	
Item 2	0.904		0.901		0.906	
Time pressure		0.858		0.858		0.858
Item 1	0.911		0.916		0.919	
Item 2	0.918		0.923		0.923	
Price consciousness		0.809		0.809		0.809
Item 1	0.663		0.667		0.662	
Item 2	0.859		0.861		0.862	
Item 3	0.916		0.923		0.922	

For customers' evaluations of each touchpoint, we used a measure on a scale from 1 ("very negative") to 7 ("very positive"). The average valence values for the touchpoints were greater than 4, so the majority of encounters were positive or at least neutral, consistent with existing literature (i.e., Chevalier and Mayzlin 2006; Rui et al. 2013; Tirunillai and Tellis 2012). The average valences (experience) of OIT touchpoints (i.e., publicity and WOM) were lower than those of the other touchpoints though, suggesting that companies had less control over these types (see Table 4.4).

Table 4.6: Variable Operationalization

Variable	Operationalization
Variables in satisfaction model (time-invariant)	
Vol.+touchpoint	The number of encounters for a touchpoint reported by a customer during the four-week tracking period
Val.+touchpoint	Average valence score for a touchpoint reported by a customer during the four-week tracking period
Variables in behavior model (time-varying)	
S. D. (state dependence) +touchpoint	State dependent variable. =1 if a customer reported an encounter of the touchpoint in the previous day; =0 otherwise
Cum.Posi.+touchpoint	The cumulative number of positive encounters (experience measure >4) for a touchpoint reported by a customer before the current day
Cum.Neg.+touchpoint	The cumulative number of negative encounters (experience measure <5) for a touchpoint reported by a customer before the current day
Time trend	=1, 2, 3, …, 28. Identifying the current day
Week	=1 if the current day is in the weekend; =0 otherwise
Pre-satisfaction and character variables in both models	
Pre-satisfaction	Average value of measurement items related to satisfaction before the real-time tracking period
Age	Age of a customer
Gender	=1 if a customer is male; =0 if otherwise
Social class	=1 if a customer belongs to ABC1 (higher class); =0 if a customer belongs to C2DE (lower class)
Education	=1 if a customer holds a college or above; =0 if otherwise
Shopping enjoyment	Average value of measurement items related to shopping enjoyment
Time pressure	Average value of measurement items related to time pressure
Price consciousness	Average value of measurement items related to price consciousness

Next, we calculated the variables in the satisfaction and behavior models (see Table 4.6). In the satisfaction model, touchpoint volume was the total number of encounters for a touchpoint in the four-week survey period; its valence was the average value on the touchpoint experience measure. Not every customer encountered every investigated touchpoint within the four-week study period, so we replaced missing data by 4, equivalent to a neutral attitude. In the behavior model, we distinguished negative touchpoint experiences (experience measure less than 4) from positive and neutral experiences (experience measure more than 3), to account for the negative asymmetric effects of touchpoints on customer behavior (Ahluwalia et al. 2000; Chevalier and Mayzlin 2006; Mittal et al. 1998).

4.4.2. Methodology

We employed linear multiple regression to estimate the effects of various touchpoint experiences on customer satisfaction:

$$Satisfaction_i = \beta_0 + \beta_1 * Pre.Satisfaction_i + \boldsymbol{Vol.TCP}_i * \boldsymbol{\gamma} + \boldsymbol{Val.TCP}_i * \boldsymbol{\delta} + \boldsymbol{Characters}_i * \boldsymbol{\theta} + \varepsilon_i \qquad \text{(Eq. 4.1)}$$

where, the satisfaction of customer i is determined by previous satisfaction ($Pre.Satisfaction_i$), a vector of touchpoint volume (frequency) variables ($Vol.TCP_i$), a vector of touchpoint valence variables ($Val.TCP_i$), and several character variables ($Characters_i$) including age, gender, social class, and education level. The number of volume or valence variables varies across categories: 8 in the supermarket category, 9 in the banking category, and 7 in the healthcare category. The term ε_i indicates individual-specific error. In Equation 1, the explanatory variables do not change over time.

This equation could create endogeneity problems, because the volumes of CIT in a month (i.e., store and online transactions) might be affected by FIT or OIT. Therefore, we conducted additional analyses to determine if the volume of CIT could be explained by the volumes of FIT or OIT. We found no such effects. Moreover, we compared the results from Equation 1 with a 2SLS, in which pre-loyalty and shopping duration served as instrumental variables. The results were very similar, suggesting that the proposed model did not suffer from endogeneity problems.

We employed univariate dynamic probit models with random effect to investigate the impact of touchpoint experiences on store transaction in the supermarket and healthcare, and a bivariate dynamic probit model with random effect to examine the effects of touchpoint experiences on online and store transaction in the banking category. Each transaction was represented by a dummy variable ($Transc_{mit}$), equal to 1 if the transaction m (m = 1, store transaction; m = 2, online transaction) happened on the current day and 0 otherwise. Because of the inertial effect (Deighton et al. 1994; Valentini et al. 2011), we allow $Transc_{mit}$ to be affected by itself in the previous period (t-1). An endogeneity problem again may arise because $Transac_{mi(t-1)}$ correlates with the random effect (Greene 2007). Therefore, we adopted the two-step dynamic probit model proposed by Heckman (1981):

Step 1 (when t=0):

In the supermarket and healthcare categories:

$$Transc_{1i0} = 1, if\ Transc^*_{1i0} > 0; 0, otherwise \qquad \text{(Eq. 4.2)}$$

In the banking category:

$$\begin{Bmatrix} Transc_{1i0} = 1, if\ Transc^*_{1i0} > 0; 0, otherwise \\ Transc_{2i0} = 1, if\ Transc^*_{2i0} > 0; 0, otherwise \end{Bmatrix} \qquad \text{(Eq. 4.3)}$$

m=1, store; m=2, online

$$\begin{aligned} Transc^*_{mi0} = {} & \beta_{m0} + \beta_{m1} * Pre.Satisfaction_i + \boldsymbol{Cum.Neg.TCP}_{i0} * \boldsymbol{\gamma_m} \\ & + \boldsymbol{Cum.Posi.TCP}_{i0} * \boldsymbol{\delta_m} + \boldsymbol{Characters}_i * \boldsymbol{\theta_m} + \beta_{m5} Time_{i0} \\ & + \beta_{m6} Weekend_{i0} + \alpha_{mi} + \varepsilon_{mi0} \end{aligned} \qquad \text{(Eq. 4.4)}$$

Step 2 (when t>0):

In the supermarket and healthcare categories:

$$Transc_{1it} = 1, if\ Transc^*_{1it} > 0; 0, otherwise \qquad \text{(Eq. 4.5)}$$

In the banking category:

$$\begin{Bmatrix} Transc_{1it} = 1, if\ Transc^{*}_{1it} > 0; 0, \textit{otherwise} \\ Transc_{2it} = 1, if\ Transc^{*}_{2it} > 0; 0, \textit{otherwise} \end{Bmatrix} \quad \text{(Eq. 4.6)}$$

m=1, store; m=2, online

$$\begin{aligned} Transc^{*}_{mit} = {} & \beta'_{m0} + \beta_{m1} * Pre.Satisfaction_i + \beta_{m2} * Transc_{mi(t-1)} \\ & + \boldsymbol{Cum.Posi.TCP}_{it} * \boldsymbol{\gamma_m} + \boldsymbol{Cum.Neg.TCP}_{it} * \boldsymbol{\delta_m} \\ & + \boldsymbol{Characters}_i * \boldsymbol{\theta_m} + \beta_{m5} * Time_{it} + \beta_{m6} * Weekend_{it} \\ & + \mu_{mi} + \varepsilon_{mit} \end{aligned} \quad \text{(Eq. 4.7)}$$

where, $Transc^{*}_{mit}$ refers to the latent utility of customer i for conducting transaction m on day t. The explanatory variables are both time-varying and time-invariant variables. In addition, $\boldsymbol{Cum.Posi.TCP_{it}}$ and $\boldsymbol{Cum.Neg.TCP_{it}}$ refer to a vector of cumulative numbers of positive and negative touchpoints before the current day. We control for the effects of the time trend ($Time_{it}$) and weekend ($Weekend_{it}$). Similar to the satisfaction model, the utility function is also affected by a set of time-invariant variables, including pre-satisfaction ($Pre.Satisfaction_i$) and a vector of customer characteristics ($\boldsymbol{Characters}_i$). Finally, μ_{mi} represents the customer-specific random effect, and ε_{mit} is the individual- and time-specific random error.

4.5. Results

4.5.1. Results of the Satisfaction Model

We built the satisfaction model sequentially, and summarized the model fit for each in Table 4.7:

Model 1: Containing only a single pre-satisfaction variable

Model 2: Including both pre-satisfaction and customer characteristics, which set up a baseline for future models.

Model 3: Adding touchpoint volume variables on the basis of Model 2.

Model 4: Adding touchpoint valence variables on the basis of Model 2.

Model 5: Adding both touchpoint volume and valence variables on the basis of Model 2.

Table 4.7: Satisfaction Model Statistics

Models	**AIC**	**BIC**	**Adj R^2**	**Avg VIF**	**Max VIF**
Supermarket category					
Model 0: Null	1313.9	1317.9	0.00%	NA	NA
Model 1: Pre-satisfaction	1104.0	1112.0	40.28%	1.00	1.00
Model 2: Baseline	1098.8	1134.9	42.03%	1.15	1.32
Model 3.1: Baseline +Volume	1095.2	1159.4	43.48%	1.16	1.33
Model 3.2: Baseline +Volume	1099.0	1163.2	42.95%	1.15	1.33
Model 4: Baseline +Valence	1026.6	1094.9*	52.31%	1.19	1.35
Model 5.1: Full Model	1018.0*	1110.3	53.95%	1.32	1.62
Model 5.2: Full Model	1020.6*	1113.0	53.66%	1.32	1.62
Banking category					
Model 0: Null	1326.3	1330.1	0.00%	NA	NA
Model 1: Pre-satisfaction	1014.1	1021.8*	59.24%	1.00	1.00
Model 2: Baseline	1019.4	1054.1	59.42%	1.13	1.30
Model 3.1: Baseline +Volume	1022.1	1087.6	60.00%	1.14	1.34
Model 3.2: Baseline +Volume	1022.0	1087.5	60.01%	1.13	1.35
Model 4: Baseline +Valence	987.5*	1056.9	63.87%	1.20	1.45
Model 5.1: Full Model	996.1	1092.4	63.66%	1.28	1.60
Model 5.2: Full Model	995.8	1092.2	63.69%	1.27	1.51
Healthcare category					
Model 0: Null	799.2	802.5	0.00%	NA	NA
Model 1: Pre-satisfaction	660.6	667.3	48.07%	1.00	1.00
Model 2: Baseline	657.2	687.5	50.49%	1.18	1.38
Model 3: Baseline +Volume	662.7	716.4	50.75%	1.18	1.43
Model 4: Baseline +Valence	603.6*	657.4*	62.67%	1.23	1.48
Model 5.1: Full Model	614.7	685.3	61.51%	1.31	1.54
Model 5.2: Full Model	608.2	678.8	62.66%	1.32	1.54

Notes: * indicates the lowest value of the corresponding index.

Some variables are highly related (>.5), e.g. between volume variables and between volume and valence variables (see Table C.4 to C.6 in Appendix C). In these cases, we split the variables in the different models (e.g., Model 3.1 and 3.2 in the supermarket and banking categories). To diagnose the existence of multi-collinearity, we calculated the variance inflation factors (VIF) for all explanatory variables in each model. As summarized in Table 4.7, all VIF values are below the cut off of 5 (O'Brien 2007), suggesting multi-collinearity is not of concern.

Model comparison. We compare above models and explanatory power of added variables on the basis of the Bayesian information criterion (BIC), Akaike information criterion (AIC) and adjusted R^2 (see Table 4.7).

We start by discussing the explanatory power of valence and volume variables. Compared with Model 2 (baseline model), the adjusted R^2 of Model 4 that contains both baseline and valence variables, improved from 42.03% to 52.31% (10.28%) in the supermarket category, from 59.24% to 63.87% (4.63%) in the banking category, and from 50.49% to 62.67% (12.18%) in the healthcare category. The adjusted R^2 of Model 3 (including baseline and volume variables) increased by only 1.45% in the supermarket category, 0.58% in the banking category, and 0.26% in the healthcare category, compared with Model 2. Therefore, touchpoint valence exerted a stronger effects on satisfaction than touchpoint volume, consistent with our expectation. Finally, pre-satisfaction exhibited strong explanatory power on predicting current satisfaction, implying a strong carryover effect from the past period (Van Doorn and Verhoef 2008; Mittal et al. 1998).

Consistent with above analysis, Model 4 (baseline and valence variables) was preferred according to AIC and/or BIC in most cases, suggesting the addition of volume variables hardly improve model performance. In the banking category, Model 1 (incl. pre-satisfaction only) had the lowest BIC value among various models but the AIC value suggested Model 4 as the best-fit model, because BIC brings more penalty than AIC with the increase of the number of explanatory variables. To compare the effects of valence variables across categories we chose Model 4 as the main model. Because Model 4 does not contain volume variables, we also report the results of Model 3 that are related to these variables. Table 4.8, 4.9 and 4.10 present the detailed model results for each category. Because we separated correlated variables in different models, Model 3 may contain two sub-models. For simplicity, we report the results of the first column (e.g., Model 3.1 for Model 3) and use the findings of the second column as the supplementary evidence.

Table 4.8: Results of Satisfaction Model in the Supermarket Category

	Model 1	Model 2	Model 3.1	Model 3.2	Model 4	Model 5.1	Model 5.2
Constance	1.723***	0.839*	0.770*	0.811	-1.820**	4.307***	4.353***
Control variables							
Pre-satisfaction	0.685***	0.658***	0.665***	0.663***	0.515***	0.523**	0.521**
Age		-0.001	0.000	-0.001	-0.003	-0.001	-0.002
Gender		0.046	0.057	0.056	0.171	0.186*	0.190*
Social status		0.123	0.14	0.143	0.068	0.099	0.098
Education		-0.092	-0.112	-0.110	-0.001	-0.012	-0.006
Shopping enjoyment		-0.021	-0.025	-0.028	-0.012	-0.017	-0.020
Time pressure		0.114**	0.102***	0.102**	0.105**	0.100**	0.099**
Price consciousness		0.096	0.101	0.101	0.068	0.076	0.075
Touchpoint volumes							
Vol. Store transaction			-0.003	-0.002		-0.013	-0.013
Vol. TV & newspaper			-0.010**	--		-0.007	--
Vol. Billboard			0.101***	0.096***		0.109***	0.104***
Vol. Direct communication			0.043	0.034		0.056*	0.049
Vol. Online banner			-0.018	-0.033		-0.018	--
Vol. In-store communication			0.023	0.012		-0.044	-0.054
Vol. Publicity			--	-0.027		--	-0.004
Vol. WOM from friends			-0.071	-0.077		-0.116	-0.124
Touchpoint valences							
Val. Store transaction					0.271***	0.279***	0.286***
Val. TV & newspaper					0.109*	0.111**	0.101*
Val. Billboard					0.124	0.011	0.020
Val. Direct communication					-0.014	-0.043	-0.046
Val. Online banner					-0.018	--	-0.013
Val. In-store communication					0.096*	0.125**	0.129**
Val. Publicity					0.141*	0.116	0.117
Val. WOM from friends					0.048	0.100	0.105

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

Table 4.9: Results of Satisfaction Model in the Banking Category

	Model 1	Model 2	Model 3.1	Model 3.2	Model 4	Model 5.1	Model 5.2
Constance	0.92	0.202	0.059	0.079	-1.706*	-1.655*	-1.401
Control variables							
Pre-satisfaction	0.828***	0.816***	0.821***	0.821***	0.703***	0.706***	0.708***
Age		0.008	0.008	0.008	0.008	0.009	0.009
Gender		0.031	0.026	0.022	0.140	0.119	0.122
Social status		-0.061	-0.017	-0.022	-0.044	-0.008	-0.015
Education		-0.16	-0.17	-0.163	-0.117	-0.123	-0.121
Shopping enjoyment		0.019	0.034	0.033	0.018	0.023	0.023
Time pressure		0.028	0.044	0.044	0.045	0.047	0.048
Price consciousness		0.055	0.036	0.035	-0.004	-0.013	-0.012
Touchpoint volumes							
Vol. Store transaction			0.021	0.021		0.006	0.006
Vol. TV & newspaper			0.004	--		-0.003	--
Vol. Billboard			0.069*	0.071*		0.058	0.056
Vol. Direct communication			-0.072	-0.072		-0.056	-0.056
Vol. Online banner			0.044	0.042		0.042	0.034
Vol. In-store communication			-0.042	-0.041		-0.001	--
Vol. Online transaction			0.027	0.027		0.003	0.003
Vol. Publicity			--	0.014		--	0.005
Vol. WOM from friends			-0.24	-0.244		-0.158	-0.170
Touchpoint valences							
Val. Store transaction					0.197***	0.194***	0.193***
Val. Online transaction					0.078	0.082	0.083
Val. TV & newspaper					0.204***	0.200***	0.199***
Val. Billboard					0.146	0.084	0.084
Val. Direct communication					0.014	0.029	0.029
Val. Online banner					0.008	-0.008	-0.001
Val. In-store communication					-0.049	--	-0.076
Val. Publicity					-0.108	-0.086	-0.077
Val. WOM from friends					0.084	0.058	0.056

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

Table 4.10: Results of Satisfaction in the Healthcare Category

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5.1**	**Model 5.2**
Constance	1.194***	0.064	-0.113	-3.551***	-2.951***	-3.506***
Control variables						
Pre-satisfaction	0.771***	0.752***	0.739***	0.605***	0.606***	0.596***
Age		0.012	0.014	0.004	0.006	0.007
Gender		0.563***	0.552**	0.614***	0.549***	0.576***
Social status		0.327	0.403*	0.326*	0.405*	0.311
Education		-0.098	-0.174	0.007	-0.029	0.024
Shopping enjoyment		0.06	0.055	0.023	0.028	0.029
Time pressure		0.048	0.039	0.037	0.051	0.037
Price consciousness		-0.029	0.003	0.015	0.077	0.041
Touchpoint volumes						
Vol. Store transaction			0.068		-0.070	-0.060
Vol. TV & newspaper			0.153		0.105	0.068
Vol. Billboard			0.048		0.018	0.004
Vol. Direct communication			-0.113		-0.114	--
Vol. In-store communication			-0.033		-0.060	--
Vol. Publicity			-0.032		-0.022	-0.023
Vol. WOM from friends			-0.026		-0.041	-0.068
Touchpoint valences						
Val. Store transaction				0.326***	0.376***	0.355***
Val. TV & Newspaper				0.057	0.034	0.005
Val. Billboard				-0.005	0.050	0.000
Val. Direct communication				0.127*	--	0.133*
Val. In-store communication				0.204	--	0.199
Val. Publicity				0.228***	0.226***	0.228***
Val. WOM from friends				0.119	0.137	0.097

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

Effects of volume variables. In most cases, touchpoints' volumes (see results related to vol. touchpoint's name) had no effect on customer satisfaction; their effects even vanished or became less significant when we added valence variables (see Model 3 vs. Model 5). For the few significant effects, we found that volumes of billboards increased satisfaction in the supermarket category (.101, p < .001) and in the banking category (.069, p <. 05). Television and newspaper volumes, however, reduced the satisfaction of the supermarket category (-.010, $p < .01$).

Effects of valence variables. For CITs (store and online purchase/usage), we found that store transaction valence increased customer satisfaction in the supermarket (.271, p < .001), banking (.197, p < .001), and healthcare (.326, p < .001) categories. In the banking category, the effect (.078) of online transaction valence was only significant at the .1 level. Therefore H_{1a} is only partially supported.

With respect to FITs, the valence of television & newspaper advertising significantly increased satisfaction for supermarkets (.109, p < .05) and banking (.204, p < .001). The valence of in-store communication was positively associated with satisfaction in the supermarket (.096, $p < .05$) and direct communication valence increased the level of satisfaction for the healthcare category (.127, $p < .05$). We did not find any significant results related to display advertising (billboard, online banner), which suggests these touchpoints failed to differentiate products or strengthen brand preferences. Therefore, the FIT valences also influenced customer satisfaction, but their effects are highly fragmented. Therefore H_{1b} is only partially supported.

The effects of the OIT valences (publicity and offline WOM) were not significant in most instances, with the exception of publicity, which positively influenced satisfaction in the supermarket (.141, $p < .05$) and healthcare category (.228, $p < .001$). Thus H_{1c} is also only partly supported. A possible explanation might be that our data span a relatively short period (four weeks), so customers had little chance to encounter sufficient number of WOMs to be strongly affected by this touchpoint.

Effects of control variables. Pre-satisfaction had a strong, positive effect on current satisfaction in all three categories. Age had no effect on satisfaction. Men were more likely to achieve higher satisfaction than women in the healthcare category (.614, p < .001). With respect to the effects of the customer characters, we found that time pressure exerted a positive effect on satisfaction in the supermarket category (.105, $p < .01$), and customers with higher social status were more likely to be satisfied in the healthcare category (.326, $p < .05$).

4.4.2. Results of the Behavior Model

We present the results of the behavior model for each category in Tables 4.11 and 4.12. Similar to the satisfaction model, we separated highly correlated variables (see Table C.7 to C.9 in Appendix C), leading to multiple columns (sub-models) of results for each model. To avoid potential confusion, we discuss the results of the first column (i.e., Model 1.1 and Model 2.1) and cite results from the other columns when needed.

Table 4.11: Results of Behavior Model in the Supermarket and Healthcare Category

	Store transaction in the supermarket		Store transaction in the healthcare	
	Model 1.1	**Model 1.2**	**Model 1.1**	**Model 1.2**
State dependence variables				
S.D. Store transaction	-0.200***	-0.200***	0.099	0.094
Cumulative previous behaviors				
Cum. Posi. Store transaction	0.077***	0.077***	-0.170***	-0.169***
Cum. Posi. WOM to friends	0.075	0.075	-0.044	-0.077
Cum. Neg. Store transaction	0.068**	0.068**	-0.158*	-0.159*
Cum. Neg. WOM to friends	-0.058	-0.058	0.113	0.121
Cumulative previous FITs				
Cum. Posi. TV & newspaper	0.000	0.000	-0.254*	-0.245*
Cum. Posi. Billboard	-0.005	-0.005	0.036	0.063
Cum. Posi. Direct communication	0.016	0.016	0.089	0.073
Cum. Posi. Online banner	-0.007	-0.007	--	--
Cum. Posi. In-store communication	-0.002	-0.002	-0.038	-0.048
Cum. Neg. TV & newspaper	0.015	0.015	0.371**	0.430**
Cum. Neg. Billboard	0.184**	0.184**	0.052	0.075
Cum. Neg. Direct communication	0.004	0.004	0.036	0.006
Cum. Neg. Online banner	0.013	0.013	--	--
Cum. Neg. In-store communication	-0.059	-0.059	0.214	0.072
Cumulative previous OITs				
Cum. Posi. Publicity	--	--	-0.027	--
Cum. Posi. WOM from friends	0.153*	0.153*	-0.141	-0.102
Cum. Neg. Publicity	--	--	--	-0.083**
Cum. Neg. WOM from friends	-0.194	-0.194	0.039	0.085
Control variables				
Pre-satisfaction	-0.007	-0.007	0.035	0.056*
Time trend	-0.021***	-0.021***	0.004	0.005
Weekend	0.057*	0.057*	-0.711***	-0.707***
Age	0.004**	0.004**	0.004	0.003
Gender	0.046	0.046	-0.226**	-0.216**
Social status	0.010	0.010	-0.264***	-0.229**
Education	-0.005	-0.005	0.120	0.100
Shopping enjoyment	-0.025	-0.025	-0.027	-0.027
Time pressure	0.006	0.006	0.036	0.033
Price consciousness	0.009	0.009	-0.004	0.026
Constance (t=0)	-1.744***	-1.744***	-2.856***	-2.871***
Constance (t>0)	-1.157***	-1.157***	-1.747***	-1.973***

Notes: FITs: firm-initiated touchpoints. OITs: other-initiated touchpoints.
$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

Table 4.12: Results of Behavior Model in the Banking Category

	Store Transaction			**Online Transaction**		
	Model 1.1	**Model 1.2**	**Model 1.3**	**Model 2.1**	**Model 2.2**	**Model 2.3**
State dependence variables						
S.D. Store transaction	-0.114	-0.156	-0.152	-0.135	-0.143	-0.141
S.D. Online transaction	-0.228	-0.228	-0.228	0.132	0.139	0.139
Cumulative previous behaviors						
Cum. Posi. Store transaction	0.074	0.019	0.025	0.080**	0.063*	0.066*
Cum. Posi. Online transaction	0.003	0.016	0.016	0.088***	0.087***	0.086***
Cum. Posi. WOM to friends	0.061	0.093	0.077	-0.026	0.063	0.054
Cum. Neg. Store transaction	-0.102	-0.121	-0.116	-0.079	-0.063	-0.058
Cum. Neg. Online transaction	0.117	0.102	0.087	-0.078	-0.030	-0.036
Cum. Neg. WOM to friends	0.017	0.053	0.046	-1.430	-1.305	-1.318
Cumulative previous FITs						
Cum. Posi. TV & newspaper	-0.019	--	--	0.007	--	--
Cum. Posi. Billboard	0.008	0.017	0.019	-0.016	-0.005	-0.005
Cum. Posi. Direct communication	-0.027	-0.036	-0.035	0.018	0.013	0.014
Cum. Posi. Online banner	0.105	0.097	0.118*	-0.013	-0.028	-0.022
Cum. Posi. In-store communication	0.163*	0.194*	0.192*	0.058	0.086	0.084
Cum. Neg. TV & newspaper	0.033	--	--	-0.034	--	--
Cum. Neg. Billboard	0.066	0.076	0.076	0.008	-0.056	-0.059
Cum. Neg. Direct communication	-0.133	-0.082	-0.085	-0.018	-0.063	-0.065
Cum. Neg. Online banner	-0.105	-0.199	-0.089	-0.282	-0.398	-0.375
Cum. Neg. In-store communication	0.197	0.281	0.299	-4.753	-4.743	-4.725
Cumulative previous OITs						
Cum. Posi. Publicity	--	0.062	--	--	0.031	--
Cum. Posi. WOM from friends	-0.080	-0.145	-0.100	0.022	0.026	0.042
Cum. Neg. Publicity	--	--	-0.043	--	--	-0.022
Cum. Neg. WOM from friends	0.203	0.139	0.139	0.151	0.159	0.163
Control variables						
Pre-satisfaction	0.036	0.040*	0.036	-0.040*	-0.034*	-0.035*
Time trend	-0.008	-0.006	-0.006	-0.034***	-0.034***	-0.033***
Weekend	-0.257***	-0.259***	-0.258***	-0.208***	-0.208***	-0.208***
Age	0.009***	0.010***	0.010***	-0.001	0.000	0.000
Gender	-0.046	0.024	0.027	-0.081	-0.010	-0.010
Social status	-0.018	-0.060	-0.041	-0.004	0.057	0.065
Education	-0.134*	-0.126*	-0.141*	0.094	0.160***	0.156**
Shopping enjoyment	-0.017	-0.019	-0.015	-0.058***	-0.075***	-0.073***
Time pressure	-0.026	-0.007	-0.009	-0.082*	-0.103***	-0.105***
Price consciousness	0.008	-0.023	-0.016	0.057***	0.093***	0.095***
Constance (t=0)	-2.551***	-2.208***	-2.275***	-1.041***	-1.223***	-1.253***
Constance (t>0)	-2.185***	-2.217***	-2.280***	-0.831***	-1.051***	-1.077***

Notes: FITs: firm-initiated touchpoints. OITs: other-initiated touchpoints.
$^{**}p < .001$. $^{**}p < .01$. $^{*}p < .05$..

Effects of state dependence. In the supermarket category, the state dependence of store transaction had a negative, significant effect on store transactions (-.200, $p < .001$). This finding is plausible as a customer is less likely to visit the supermarket if she or he just shopped the previous day. Apart from this case, the state dependence variables did not affect customer behavior.

Effects of cumulative transaction (CIT) experiences. The negative and positive transaction experiences in the past period had very similar effects on the incidence of current transaction. Specifically, previous positive experiences with store transactions increased the likelihood of current store transaction in supermarkets (.077, $p < .001$), and negative store transactions exerted a similar positive effect (.068, $p < .01$). For banking, the number of positive store transactions (.080, $p < .01$) and positive online transactions (.088, $p < .001$) in the past also positively impacted the incidence of online transaction. In the healthcare category, positive store transactions (-.170, $p < .001$) and negative store transactions (-.158, $p < .05$) reduced the incidence of current store transaction. This unexpected result is most likely caused by the category difference. The more frequently a patient visits the doctor, the more likely he or she is to recover and stop visiting. Therefore, our results partially support H_2 and H_{3a}. No support is provided for H_{3b}.

Effects of cumulative FIT and OIT experiences. Positive experiences with in-store communications in the past increased the incidence of store transactions for banking (.163, $p < 0.05$) and negative experiences with supermarket billboards enhanced the likelihood of store transactions (.184, $p < .01$). Furthermore, negative experiences with television and newspaper also increased the probability of transactions in healthcare (.371, $p < .01$), positive experiences with television and newspaper advertising reduced the transaction incidence in healthcare (-.254, $p < .05$). Together these results provide no support for H_4.

With respect to the effects of OIT experiences, customers were more likely to shop in supermarkets if they received positive WOM from their friends (.153, $p < .05$). A negative experience with publicity reduced the incidence of visiting hospitals (-.083, $p < .01$, Model 2.2). As such these results provide partial support for H_5 and H_6.

Effects of control variables. Results of pre-satisfaction was not consistent across sub-models for each model in most cases. The only exception is the pre-satisfaction in the banking category, which exerted a negative effect on the probability of using online banking service (-.040, p < .05). A negative relationship arose between the time trend and transaction in supermarket and banking categories, probably because customers sent more messages at the beginning of the survey period than at the end. The weekend variable also increased the incidence of supermarket purchases (.057, $p < .05$) but reduced the probability of bank branch visits (-.257, $p < .001$) and clinic visits (-.711, $p < .001$), consistent with the traditional operating hours for the three categories. Age had a positive effect on the incidence of supermarket store transactions (.004, $p < .05$) and the chance of visiting bank branches (.009, $p < .001$), probably because older people tend to have more free time. However, these older respondents were less likely to speak with others about their shopping experiences in the supermarket (-.022, $p < .001$) or their healthcare experiences (-.029, $p < .001$) than younger people. Gender did not affect customer behavior, with one exception: Women were more likely to see doctors than men (-.226, $p < .01$).

The effects of the psychographic variables varied across categories. In the banking category, customers with more education were less likely to visit bank branches (-.134, $p < .05$). Customers were more willing to use Internet banking if they had lower requirements related to shopping enjoyment (-.058, $p < .001$), were less sensitive to time pressures (-.082, $p < .05$), or were more price conscious (.057, $p < .001$). The results in the healthcare category show that customers with higher social status were less likely to visit the hospital (-.264, $p < .05$) and more likely to talk with their friends about a supermarket brand (.533, $p < .05$).

We summarize the findings of hypothesis testing in Table 4.13.

Table 4.13: Summary of Results for Hypothesis Testing

Hypothesis	**Results**
H_{1a}: CIT valence increases customer satisfaction.	Partially supported
H_{1b}: FIT valence increases customer satisfaction, only if the FIT contains information that promotes brand differentiation.	Partially supported
H_{1c}: OIT valence increases customer satisfaction.	Partially supported
H_2: Positive instant experiences with previous CITs increase the frequency of current transactions.	Partially supported
H_{3a}: Negative instant experiences with previous transactions (CITs) increase the frequency of current transactions.	Partially supported
H_{3b}: Negative instant experiences with previous transactions (CITs) reduce the frequency of current transactions.	Not supported
H_4: Both positive and negative instant experiences with previous FITs increase the frequency of current transactions.	Not supported
H_5: Positive instant experiences with previous OITs increase the frequency of current transactions.	Partially supported
H_6: Negative instant experiences with previous OITs reduce the frequency of current transactions.	Partially supported

4.5. Discussion and Implications

4.5.1. Theoretical Implications

Effects of multi-touchpoint experiences on customer satisfaction

Table 4.14 summarizes the main findings from the satisfaction model. The effect of customers' touchpoint experiences on satisfaction mainly comes from the valences of touchpoints, and not from their volumes. The valences of store transactions increase satisfaction in all three categories, whereas the valence effects of FITs and OITs vary across types and categories. We detail the theoretical implications of these findings below.

Table 4.14: Summary of the Main Findings in the Satisfaction Model

Type	Measure	Supermarket	Banking	Healthcare
Customer-initiated (H1a)	FRE.	N.S.	N.S.	N.S.
	VAL.	Store transaction (+)	Store transaction (+)	Store transaction (+)
Firm-initiated (H1b)	FRE.	TV & newspaper (-), Billboard (+),	Billboard (+)	N.S.
	VAL.	TV & newspaper (+), In-store communication (+)	TV & newspaper (+)	Direct communication (+)
Other-initiated (H1c)	FRE.	N.S.	N.S.	N.S.
	VAL.	Publicity (+)	N.S.	Publicity (+)

Notes: FRE.: frequency; VAL.: Valence; N.S.: non-significant effect; +: positive effect; -: negative effect.

Previous studies suggest that the volumes of touchpoints that customers experience during their shopping trips can affect brand satisfaction (Van Doorn and Verhoef 2008; Maxham and Netemeyer 2002). Our research reveals that volume effects are virtually insignificant compared with the effects of touchpoints' valence in determining customer satisfaction. Researchers and practitioners thus should focus on the valence when investigating the effects of touchpoints on customer satisfaction.

We also uncover several distinct features with respect to the effects of CIT, FIT, and OIT experiences. The valence of CITs (i.e. store transaction) exerts strong and positive effects on satisfaction, and these impacts are significant in all three categories. These findings are consistent with the existing evidence that reveals the perceived quality of a customer's experience with the product or service exerts a strong impact on satisfaction (Anderson et al. 1994; Mittal et al.

1998; Oliver and DeSarbo 1988). We notice that the volume of television and newspaper has either a negative effect on customer satisfaction in the supermarket category or no effect in the other categories, whereas the volume of billboard exerts a positive effect on the satisfaction of the banking and no effect in other two categories. A possible explanation is that customers need allocate more resources (e.g., time and money) to get access the content provided by companies in television and newspaper than the billboard. Therefore, if the company delivered too many messages (e.g. advertising) through television and newspaper without providing valuable information, customers might feel that they are wasting time and money thus are less satisfied with the company.

In contrast, the effects of FIT and OIT valence vary across categories and are mostly not significant. For supermarkets and banking, the valence of television and newspaper FIT greatly increases customer satisfaction. For billboards though, volume instead of valence increases satisfaction in these two categories. The varied effects likely arise because these two touchpoints carry different information contents: television advertising provides details about brand attributes and other associations that enhance product differentiation, whereas billboard advertising serves as a reminder prior to purchase (Mitra and Lynch 1995; Norris 1984). We subsequently posit that the valence of FIT may increase customer satisfaction if the touchpoint helped strengthen brand preferences and differentiates products, because the enhanced brand preference reduces price elasticity and increases customer satisfaction (Anderson et al. 1994; Fornell et al. 1996; Mitra and Lynch 1995). The findings with respect to the valence effects of television and newspaper confirm this expectation and further suggest only valence (not volume) of this type of touchpoints strengthening brand preference. In-store communication in the supermarket category and direct communication in the healthcare category serve the same function as television and newspaper. The positive effect of billboard volume reveal that reminder type of FIT may promote customer satisfaction, but only through its volume and with very minor explanation power. With respect to the effects of OITs, only the valence of publicity has a positive effect on satisfaction.

Effects of multi-touchpoint experience on customer behavior

We summarize the main findings of the behavior model in Table 4.15. We find that both positive and negative experiences with previous transactions (CITs) increase the frequency of current transaction in the supermarket category, whereas both experiences with healthcare agencies reduce the incidence of hospital or clinic visit by the patient. The effects of FIT experiences vary highly across categories. Moreover, positive OIT experiences in the form of WOM can enhance transaction incidence in supermarkets, and the negative OIT of publicity reduces the frequency in the banking category.

Table 4.15: Summary of the Main Findings in the Behavior Model

		Store transaction			**Online transaction**
Touchpoint Type	**Measure**	**Supermarket**	**Banking**	**Healthcare**	**Banking**
Previous transaction (Customer-initiated)	P.T. (H2)	Store transaction (+)	N.S.	Store transaction (-)	Store transaction (+), Online transaction (+)
	N.T. (H3a, H3b)	Store transaction (+)	N.S.	Store transaction (-)	N.S.
Firm-initiated	P.T. (H4)	N.S.	In-store communication (+)	TV & Newspaper (-)	N.S.
	N.T. (H4)	Billboard (+)	N.S.	TV & Newspaper (+)	N.S.
Other-initiated	P.T. (H5)	WOM from friends (+)	N.S.	N.S.	N.S.
	N.T. (H6)	N.S.	N.S.	Publicity (-)	N.S.

Notes: P.T.: positive touchpoint; N.T.: negative touchpoint;
N.S.: non-significant effect; +: positive effect; -: negative effect.

In line with extant literature on habitual effect (Aarts et al. 1998; Limayem et al. 2007; Wood et al. 2002), our finding confirms that people are driven by their habit and tend to repeat their previous positive transaction experiences in supermarkets and banking. Furthermore, customers continue their previous transactions in the supermarket category even after recent negative experiences related to these behaviors. The habitual effect suppresses the potential negative influence of bad experiences, probably because we investigate customers' behaviors in a short period and with a familiar brand, representing a constant environment. A meta-analysis of Ouellette and Wood (1998) reveals that customers repeat well-practiced behaviors in constant contexts without cautious decision making, because the processing that initiates and controls their performances becomes automatic. Our research thus confirms their proposition and further suggests that customers tend to temporarily ignore their negative experiences with previous experiences in such contexts. However, customers do not always follow their past behavioral traits. Both previous positive and negative experiences with healthcare agencies reduce the probability of hospital or clinic visit, probably because patients would attenuate the chance of visiting doctors if they have received enough treatment or stop doctor visit if their diseases have been cured.

Previous positive experiences with particular FITs and OITs can increase the frequency of customer shopping behavior, except that positive experiences with FITs (television and newspaper) in the healthcare category reduce transaction incidence. A post-hoc explanation might be that the television and newspaper advertisements in the healthcare category normally contain the contents related to disease information or services supplied by healthcare providers. Because people visit healthcare agencies for healthcare consult and information query in most cases, television and newspaper advertising that contains more useful information and is likely perceived as a positive experience could reduce the visit frequency.

Furthermore, the negative experiences with certain FITs (i.e., billboards in supermarkets and TV & newspaper in healthcare) and OITs (i.e., publicity in the healthcare) have different effects. Customers evaluate a FIT experience as negative, normally when they find the information carried by the FIT is unattractive or irrelevant to their shopping purpose. Our research reveals that these negative FIT experiences can still service as reminders, which helps enhance brand awareness thus shopping frequency. Different from the FIT experience, customers could perceive a OIT experience as negative, if the OIT message contained bad news or negative opinions on the brand from journalists or publics. Consistent with previous studies (Huang and Chen 2006; Tybout et al. 1981), our research suggests that the negative publicity could harm product evaluations and therefore reduce sales.

4.5.2. Managerial Implications

We offer several important managerial implications related to managing customer multi-touchpoint experiences in business markets. First, managers should focus on stimulating or creating positive emotions or touchpoint experiences, rather than increasing the number of encounters for each touchpoints. Our research suggests that customers' instant emotion evoked by multiple touchpoints with firms plays a major role in determining customer satisfaction, and their positive touchpoint experiences are more likely to enhance store transactions. Therefore, creating positive touchpoint experiences could strengthen customer relationships and promote sales or transactions. However, managers should also account for the special features of certain touchpoints. For example, customer satisfaction can be increased by the valence of television and newspaper instead of its volume, and by the volume of billboard rather than its valence. Therefore, firms should focus on improving the quality or attractiveness of the advertisements delivered through television and newspaper, and setting up more billboards on the road.

Second, compared to paid and earned touchpoints, it is more crucial for managers to enhance the experiences of customer-initiated touchpoints – customer' transaction experiences in brick-and-mortar and online stores. The online and offline transaction experiences affect not only customer satisfaction but also customers' intentions of product purchase or service usage in subsequent occasions.

Third, managers should be aware that the effects of multiple touchpoint experiences on customers' attitudes and behaviors vary greatly across different categories. For instance, to improve customer satisfaction, firms in the supermarket and banking categories should invest more resources in paid mass touchpoints (television, newspaper, and billboard) or in-store communications; healthcare companies should focus on improving their e-mail and SMS contacts with customers or their public images. Understanding customer multi-touchpoint experiences in specific contexts helps firm design category-specific strategies and maximize the efficiency of their marketing activities.

4.5.3. Limitations and Further Research

Our research suffers from several limitations that indicate further research related to the effects of multi-touchpoint experiences on customers' attitudes and behaviors. First, we trace customers' instant touchpoint experiences and transactions within a four-week period. This relatively short period makes it difficult to observe any shifts in customers' relationships with firms, such as contract termination or service updates. Further research thus should use a longer data period to investigate the effects of multi-touchpoint experiences on the long-term customer–firm relationships and shopping behavior. Second, we investigate customer behavior in several categories, all of which represent business-to-customer contexts. It would be worthwhile to conduct similar research in other categories or in business-to-business markets. Third, we focus on touchpoints that produced sufficient observations during the survey period, which limits the scope of our research. Additional research could include a broader range of touchpoints, such as call centers, online social networks, search engines, and referral websites.

Last but not the least, we investigate the effect of customer touchpoint experiences on customer purchases and usage. As revealed by previous research, customers experience multiple shopping phases during their shopping trips, including not just purchase or use but also information search and after-sales considerations (Konuş et al. 2008; Neslin et al. 2006; Puccinelli et al. 2009). Understanding and creating superior customer experiences throughout the entire buying process might generate more opportunities for firms to enhance customer satisfaction and retail performance (Puccinelli et al. 2009). Additional research thus could replicate our study for other shopping stages, such as information search or the use of after-sales services.

CHAPTER 5

Discussions and Conclusions

The objective of this dissertation was to advance existing knowledge on new channel introductions and multichannel customer behavior. Moreover, this dissertation also investigated the effects of instant multi-touchpoint experiences on customer satisfaction and behavior. This final chapter summarizes and discusses the results of the three empirical studies. The chapter continues with the theoretical and practical implications of the dissertation as a whole, and concludes with a discussion of limitations and directions for further research.

5.1. Synopsis

The main objective of this dissertation is to gain a deep understanding of new online channel adoption and customer experiences in the multi-touchpoint environment. Three empirical studies are conducted, which focuses on different aspects of multichannel and multi-touchpoint customer management. Study 1 in chapter 2 explored customer purchase amount among the segments that adopt a new online channel at different times and investigated the effects of new online channel adoption on purchase volumes in different segments. Study 2 in chapter 3 investigated the effects of cross-channel competition on channel migration and firm purchase volume. Study 3 in chapter 4 explored the influence of customer experiences with multiple touchpoints on customer satisfaction and behavior.

In this chapter, I will first summarize the key findings of the three studies. After that, I will present the theoretical and managerial implications with respect to these findings. Finally, this chapter concludes with the discussion of limitations and future research directions.

5.2. Key findings

5.2.1. Study 1: The Hare and the Tortoise: Do Earlier Online Channel Adopters Purchase More?

To explore customer purchase amount and customers' varying responses to new online channel introduction, study 1: (i) segmented customers on the basis of their purchase amount before adoption and channel adoption duration, and; (ii) examined the effects of online channel adoption on purchase volume across the identified segments.

Study 1 reveals that the heaviest shoppers are neither innovators nor early adopters of a new online channel but rather the late majority segment both before and after the adoption of a new online channel. In addition, the effects of online channel adoption on purchase volumes vary across different segments after eliminating the self-selection bias. Specifically, adoption of a new online channel does not influence the purchase volumes of heavy shopper segments (late majority and innovators). Customers in these two segments simply move a proportion of their demand from existing offline channels to the new online channel, such that the new online channel cannibalizes purchases from offline channels. However, customers in light shoppers segments (early adopter, early majority, and laggard) tend to increase their purchase volumes after adopting, and their additional volumes appear to derive mainly from sales in the new online channel.

5.2.2. Study 2: Customer Channel Migration in the Competitive Environment: the effects of Cross-Channel Competition

To explore the effect of cross-channel competition on channel adoption and purchase volumes after adoption, study 2: (i) examined the effects of customers' previous purchases from competitors' channels on their adoption of a new online channel and channel migration, and; (ii) investigated the effects of online channel adoption on purchase volumes from competitors.

Study 2 finds that customers' previous purchases from competitors' channels affect their current channel choice of the focal firm. Customers with higher preferences for competitors' online channels before the new online channel introduction are more likely to migrate to the new online channel. Customers do not always follow their past channel state dependence when switching from competitors to the focal firm. If a customer shopped from competitors' offline channels in the last month, he or she is more likely to choose the new online channel instead of the offline channels when purchasing with the focal firm.

Moreover, existing and new customers respond differently to the new online introduction and competitors' channels. Compared to new customers who are acquired after the introduction, existing customers are more likely to purchase through the existing catalog channel rather than from the new online channel, and to be affected by their previous purchases from competitors' online channels. Last but not the least, the adoption and use of new online channel reduce purchase frequencies of competitors, but increase purchase frequencies of the focal firm, both for existing and new customers.

5.2.3. Study 3: How Do Instant Multi-Touchpoint Experiences Affect Satisfaction and Behavior? A Real-Time Experience Tracking Approach

To explore the influence of customers' holistic multi-touchpoint experiences on customer attitude and behavior, study 3: (i) proposed a touchpoint typology consisting of customer-initiated touchpoints (CITs), firm-initiated touchpoints (FITs), and other-initiated touchpoints (OITs) and; (ii) investigated customers' instant and holistic experiences with these touchpoints on customer satisfaction and transaction (incl. product purchase and service usage).

Study 3 defines CITs as the encounters that are initiated by customers, covering product purchases and services usage through online and offline channels. FITs refer to the encounters that are initiated by firms, consisting by television & newspapers, billboards, online banners, and direct communications, as well as advertising in-store communications. Finally, OITs in this research include offline WOM and publicity.

This study reveals that the effect of customers' previous touchpoint experiences on satisfaction mainly comes from the valences of touchpoints, not from their volumes. The valence of CIT in-store transactions increases satisfaction in all three investigated categories (supermarket, banking and healthcare) whereas the valence effects of FIT and OIT vary highly across categories and are mostly not significant. A notable finding is that the valence of television and newspaper FIT increases customer satisfaction in the supermarket and banking categories but that the volume of this touchpoint has a negative effect in the supermarket category. For billboards though, volume instead of valence increases satisfaction in the supermarket and banking categories. With respect to the effects of previous touchpoint (CIT) experiences on customer transactions, both previous positive and negative transaction experiences can increase the incidence of current transaction in the supermarket category, but the results of FIT and OIT experiences are extremely fragmented across the three categories.

Table 5.1 outlines each study's subject, data, method and key findings.

Table 5.1: Outline of the Key Findings

	Study 1	**Study 2**	**Study 3**
Subject	Customer purchase amount and effects of new online channel adoption on purchase volumes across segments	Effects of cross-channel competition on channel migration and purchase volumes after adoption	Effects of holistic multi-touchpoint experiences on attitude and behavior
Data	Longitudinal transactional data	Longitudinal transactional data	Longitudinal survey data
Method	• Latent class analysis • Propensity score matching • Difference-in-difference analysis • Type II Tobit model	• Multivariate probit model with sample selection • Type II Tobit model	• Dynamic bivariate/univariate probit model • linear regression • Principle component analysis
Key findings	• Late majority segment purchases more than other segments; • Online channel adoption has no effect on the purchase volumes of light shopper segments; • Online channel adoption increases the purchase volumes of heavy shopper segments.	• Preference to competitors' online channels increases new online channel adoption; • Above effect has a greater impact for new customers; • Existing customers are more likely to purchase through the existing catalog channel; • State dependence of competitors' offline channels increases new channel adoption and usage; • Online channel adoption and usage reduce purchase frequencies from competitors, and increase purchase frequencies from the focal firm.	• Effect of multi-touchpoint experiences on satisfaction mainly comes from the valences of touchpoints, rather than their volumes; • Valences of in-store transactions increase satisfaction in all categories, whereas the valence effects of FIT and OIT vary strongly across types and categories; • Previous positive store transaction (CIT) experiences in supermarkets and banking increase the incidence of current transactions; Previous positive store transaction experiences in healthcare reduce the incidence of current transactions; • Previous negative store transaction experiences in supermarkets increase incidence of current transactions; Previous negative store transaction experiences in healthcare

reduce the incidence of current transactions;

- Effect of previous experiences with FITs and OITs on incidence current transactions is fragmented across categories and mostly non-significant.

5.3. Theoretical Contributions

This dissertation provides implications and contributions to three separated but highly related research streams: (1) multichannel and multi-touchpoint customer management, (2) customer experience management, and (3) innovation management.

5.3.1. Contributions to the Literature of Multichannel and Multi-touchpoint Customer Management

This dissertation contributes to the multichannel and multi-touchpoint customer management research in several ways. First, study 1 explores the relationship between purchase volumes and adoption duration, and study 2 shows how customers' previous purchases from competitor' channels on their new channel adoption and channel choices. Extant literature has broadly explored the antecedents of customers' channel choice and their adoptions of new (online) channels (Blattberg et al. 2008; Neslin et al. 2006), whereas the potential influence of customer heterogeneity and competitors' channels is almost untapped. The dissertation thus contributes to the research on customer channel choice and new channel adoption. Findings of both studies reveal that heavy shoppers or existing customers have the tendency to keep shopping from offline channels; such a tendency may lengthen their adoption duration of a new online channel and influence channel migration after the introduction of the new channel. Customers' previous purchases from competitors' online and offline channels also drive their current channel choices. These findings offer useful insights on how to successfully introduce new channels and how to effectively coordinate new channels with existing channels.

Second, the dissertation also contributes to the literature of multichannel customer management by investigating the consequences of new online channel adoption, such that its effects on customers' purchase volumes across various segments that adopt at different times (study 1) and purchases from competitors (study 2). Previous research suggests two opposing mechanisms that could influence customers' purchases after they adopt a new channel: intrinsic benefits of online shopping and marketing communications (Ansari et al. 2008; Montoya-Weiss et al. 2003; Neslin et al. 2006). The different responses to online channel introduction across segments provide the empirical evidence on the predominant effect of intrinsic benefits on customer purchases. Moreover, online channel adoption reduces purchase frequencies from competitors, both for a firm's new and existing customers. Findings of this dissertation thus can help firm design different strategies to address segment-specific challenges and offer implications on managing customer behavior in a multichannel, competitive environment.

Last but not the least, the dissertation contributes to the existing literature of multi-touchpoint customer management by exploring customer experiences with various touchpoints that they may encounter during their shopping trips, including not only the online and offline channels, but also mass media, direct contacts, publicity and word-of-mouth (study 3). Such research thus enhances our understanding of multi-touchpoint customer experience and helps firms allocate resources optimally across various marketing channels and touchpoints.

5.3.2. Contribution to the Literature of Customer Experience Management

This dissertation (study 3) offers several implications to the literature of customer experience management. First, the dissertation is the first to investigate the instant and dynamic effects of customer experiences with various touchpoints on customer satisfaction and behavior. Although recent research emphasizes the importance of creating superior customer experience, especially the holistic brand experience (Lemke et al. 2011; Meyer and Schwager 2007; Verhoef et al. 2009), very few studies empirically investigate the effect of instant multi-touchpoint experience on customer attitude or behavior (Gentile et al. 2007). Findings of this research provide valuable insights on understanding holistic customer experience and its influence.

Second, the research contributes to the research on customer experience management by introducing a novel and mobile-based real-time data collection method. This method largely resolves the memory recall problem that hinders conventional survey methods (Macdonald et al. 2012; Wirtz et al. 2003), and can track individual customer experiences across a wide range of touchpoints, extending the limits imposed by transactional, media spending, or online clickstream data (Macdonald et al. 2012; Wilson et al. 2013).

Finally, the dissertation distinguishes between a touchpoint's valence and volume effects, and explores these effects across various categories. The findings show that valence influences customer satisfaction and behavior. A deep understanding of above issues helps firms leverage their spending between a touchopoint' quality and quantity, and accommodate the category differences.

5.3.3. Contribution to the Literature of Innovation Management

The dissertation also contributes to the literature of innovation management in the area of innovation adoption. Since 1960s, extensive studies devote to investigate the antecedents and consequences of innovation adoption and diffusion, focusing mostly on new products and services (for a review, see Mahajan, Muller, and Bass 1990; Rogers 2003). Different from the adoption of new products and services, a large proportion of customers continue to purchase from the existing channel and become multichannel shoppers after adopting a new channel (e.g., Ansari et al. 2008; Deleersnyder et al. 2002; Montoya-Weiss et al. 2003; Thomas and Sullivan 2005). Apart from previous studies pertaining to customer adoption of new channels, a number of research gaps still exist, such as the shopping behavior and characteristics in different adopter segments (study 1), and the impact of online channel adoption on individual purchase volumes across segments and from competitors (study 1 and 2). These researches offer implications for firms that introduce new online channels or other types of new channels, such as mobile and social media.

5.4. Managerial Implications

The findings in this dissertation have implications for managers in their efforts to develop multichannel customer management strategies and create superior customer experience. The previous chapters detail the practical implications of each individual study. This section thus focuses on the overall implications of this dissertation with respect to the managerial perspectives.

Managers should be fully aware the effects of customer heterogeneity on customer shopping behavior and the importance of developing the segment-specific strategies, if they plan to introduce new channels. For example, to target heavy shoppers, managers should not solely focus on earliest adopters (e.g., innovators), but more importantly, they should target the customers who adopt during the middle-late period (late majority segment). Because heavy shopper segments respond to a new online channel introduction differently from the light shopper segments, marketer should differentiate their strategies between the two kinds of segments. In the former group, managers should focus on stimulating their online shopping volumes, whereas for the latter group of customers, retailers should work on improving their perceptions of the benefits of online shopping, instead of pushing them rashly to shop online. A firm’s existing and new customers also have distinct responses to the online channel introduction, such that existing customers are more likely to purchase from the firm’s existing offline channels and less likely to migrate to the new online channel. Therefore, managers may consider retaining their relationship with existing customers through the well-established offline channels and investing more marketing resources on promoting the online sales from new customers.

The findings of this dissertation also provide guidance for firms that introduce new online channels later than competitors. The dissertation suggests that managers should not hesitate to introduce their own online channels when competitors have already done so, because by adopting the new online channel existing and new customers reduce their purchases from competitors but increase purchases from the focal firm. But managers should realize that customers' previous purchase from competitors' channels could affect channel migration, and promote customer adoption of the new online channel, especially the online adoption by existing customers. Knowing customer preference for competitors' channels (e.g., through survey) helps managers predict customer channel migration after the introduction of a new channel.

Finally, this research offers valuable insights into how firms could manage customer experiences across a broad range of touchpoints. In general, managers should invest more assets on touchpoint quality instead of touchpoint quantity to enhance customer satisfaction and shopping frequencies. But they should also notice that their choice between a touchpoint's quality and quantity could vary across touchpoint types. For example, our findings suggest that managers should focus on the quality of television and newspaper advertising, but the quantity of billboards. Moreover, managers should be aware that the effects of touchpoint experiences vary greatly across categories.

5.5. Limitations and Further Research

While the dissertation provides valuable insights from both theoretical and practical perspectives, there are several limitations that point to the directions for further research. As the study-specific limitations have been well discussed in chapter 2 to 4, this section focuses on the limitations that cut across the separate studies.

First, limited by data availability, the research in study 1 and 2 lacks the information about marketing communications and does not involve the brick-and-mortar store as a sales channel. Consequently, study 1 detects the effects of marketing on customer purchases only through indirect inferences. Besides, lacking the store channel prevents the generalization of the findings from both studies. Therefore, further researches could integrate marketing communications and the store channel into the research frameworks of the two studies.

Second, all three studies investigate the effects of various factors on customers' purchases of products or use of services. Researchers and marketers have long recognized that a purchase is far more than a solitary event when the actual transaction between shoppers and retailers takes place. A customer's shopping journey consists of the multiple phases, including information search, purchase or use, and after-sales considerations (Konuş et al. 2008; Neslin et al. 2006; Puccinelli et al. 2009). As customers may have various channel preferences and their multichannel shopping behaviors vary across the multiple phases of the shopping process (Neslin et al. 2006), additional research may extend the research in this dissertation by considering customer behavior in the other shopping phases.

Third, this dissertation also has a limitation with regard to the generalizability of the results in other categories and industries. Study 1 and 2 focus on a single industry, such as natural healthy and home decoration. Study 3 investigates customers' multi-touchpoint experiences in the categories of supermarkets, banking and healthcare. The findings in study 3 indicate that customers' multi-touchpoint experiences and behavior vary greatly across categories, which is consistent with extant research on the influence of category- or industry-specific differences on multichannel customer behavior (Gensler, Leeflang, et al. 2012; Konuş et al. 2008). Accordingly, further research could apply the research in this dissertation in other contexts (products, industries, or countries).

Fourth, all investigated studies rely on the data from a single source. The research of study 1 and 2 deals with customer transactional data, which involves large samples and long-term periods but does not contain information with respect to customers' attitudes or psychographics. Study 3 employs a new real-time self-reporting approach that demonstrated its superiority over conventional survey methods in certain aspects (Macdonald et al. 2012), but this method still suffers from problems pertaining to subjective biases and low frequencies of several touchpoints. In addition, all three studies do not contain online user-generated contents (i.e., blogs and social networks) that become increasingly important to understand and predict customer shopping behavior (Chevalier and Mayzlin 2006; Stephen and Galak 2012; Trusov et al. 2009). A customer's multichannel shopping decision follows a dynamic process and is affected by every touchpoint or contact experienced during the process. Therefore, future research that can integrate multiple data sources, such as customer experience data, daily transactional data, and online social media, would add a great avenue to the research on multichannel and multi-touchpoint customer management.

Finally, the proliferation of mobile channels also offers great opportunities for ongoing research. For instance, further studies could investigate how customers respond differently to the new mobile channel introduction or the effect of cross-channel completion on mobile channel adoption and the migration between mobile and the other channels. Apart from investigating customer shopping behavior through the mobile channel, study 3 also suggests researchers could use the mobile device as a tool to collect timely customer data. Future research thus could adopt the mobile-based data collection method to study customer behavior and experience in other contexts.

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Table A.1: Profiles of Segments (full sample)

Label	**Innovator (*N*=182, 11.03%)**				**Early Adopter (*N*=320, 19.39%)**				**Early Majority (*N*=540, 32.73%)**			
	M	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**
Indicators												
Adoption duration	20	6	3	30	47	7	31	65	73	8	57	86
Yearly purchase amount before online adoption	165.68	142.36	13.26	853.33	133.84	115	10.21	686	100.29	60.48	1.02	287.56
Active Covariates												
Age	44	8	21	68	44	10	20	76	43	9	20	71
Gender (male)	4.95%				5.94%				2.78%			
Inactive Covariates												
Yearly purchase amount after online adoption	145.57	128.05	15.19	1179.07	161.65	207.83	12.79	2197.17	142.52	150.74	13.78	2434.43
Online shopping preference	0.624	0.105	0.205	0.857	0.597	0.126	0.124	0.843	0.586	0.105	0.070	0.805

Label	**Late Majority (*N*=137, 8.30%)**				**Laggard (*N*=471, 28.55)**			
	M	**SD**	**MIN**	**MAX**	**M**	**SD**	**MIN**	**MAX**
Indicators								
Adoption duration	90	13	64	120	102	10	86	124
Yearly purchase amount before online adoption	457.29	292.21	21.03	2196.48	94.45	62.34	5.94	276.11
Active Covariates								
Age	53	11	29	91	43	9	22	88
Gender (male)	0.73%				2.12%			
Inactive Covariates								
Yearly purchase amount after online adoption	472.72	522.05	48.69	3807.73	160.93	147.67	17.14	1088.94
Online shopping preference	0.223	0.150	0.000	0.654	0.570	0.110	0.163	0.792

Table A.2: DID Analysis (full sample)

	Online Adopters			Offline Customers		
	Before	After	Change	Before	After	Change
Innovator						
Total purchase amount	123.40	147.94	24.54*	117.51	141.14	23.63
(in Euros)	(160.75)	(183.66)	(182.15)	(182.80)	(190.96)	(233.42)
Total transactions	1.33	1.65	0.32*	1.31	1.48	0.16
	(1.63)	(1.85)	(1.90)	(1.87)	(2.02)	(2.39)
Offline purchase amount	123.40	65.51	-57.89*			
(in Euros)	(160.75)	(116.43)	(163.36)			
Offline transactions	1.33	0.72	-0.60*			
	(1.63	(1.12)	(1.57)			
Early adopter						
Total purchase amount	115.54	163.73	48.19*	141.83	162.92	21.09
(in Euros)	(160.23)	(230.23)	(220.10)	(201.34)	(221.11)	(218.27)
Total transactions	1.25	2.00	0.75*#	1.55	1.93	0.38
	(1.65)	(2.86)	(2.72)	(2.29)	(2.58)	(2.34)
Offline purchase amount	115.54	99.17	-16.37			
(in Euros)	(160.23)	(174.51)	(179.75)			
Offline transactions	1.25	1.16	-0.09			
	(1.65)	(2.08)	(2.08)			
Early majority						
Total purchase amount	93.08	180.37	87.29*#	129.80	127.72	-2.08
(in Euros)	(138.24)	(277.34)	(276.50)	(178.59)	(176.83)	(211.64)
Total transactions	1.10	2.00	0.90*#	1.45	1.48	0.03
	(1.57)	(3.19)	(3.12)	(1.87)	(1.87)	(2.24)
Offline purchase amount	93.08	108.74	(15.66			
(in Euros)	(138.24)	(229.51)	(241.42)			
Offline transactions	1.10	1.17	0.06			
	(1.57)	(2.60)	(2.67)			
Late majority						
Total purchase amount	483.38	432.77	-50.62	361.65	311.89	-49.76
(in Euros)	(411.63	(435.77)	(398.21)	(437.53)	(406.54)	(322.57)
Total transactions	5.60	5.26	-0.34	4.31	3.69	-0.62
	(4.85)	(5.39)	(4.65)	(5.46)	(4.54)	(2.98)
Offline purchase amount	483.38	343.58	-139.80*			
(in Euros)	(411.63)	(365.85)	(431.03)			
Offline transactions	5.60	4.06	-1.54*			

	(4.85)	(4.26)	(5.05)			
Laggard						
Total purchase amount	83.70	150.76	67.05$^{*\#}$	118.75	129.92	11.17
(in Euros)	(132.63)	(272.95)	(279.45)	(164.15)	(192.15)	(203.42)
Total transactions	1.00	1.86	0.86$^{*\#}$	1.40	1.57	0.17
	(1.53)	(2.75)	(2.73)	(1.69)	(2.09)	(2.04)
Offline purchase amount	83.70	82.90	-0.80			
(in Euros)	(132.63)	(172.23)	(178.44)			
Offline transactions	1.00	0.99	-0.01			
	(1.53)	(1.74)	(1.73)			

Notes: This table provides the means, with the standard deviations in brackets.
*Significantly different from 0 at least at the 10% level.
$^{\#}$The change in the variable for online adopters is significantly different from the change for offline customers (control group) at least at the 10% level.

Table A.3: Purchase Incidence Model (24 months and full sample)

Variable	**Innovator**	**Early Adopter**	**Early Majority**	**Late Majority**	**Laggard**
Postadoption	0.081	0.080*	0.071*	-0.097	0.087*
Postadoption × Treated group	-0.048	-0.017	0.124**	0.029	0.004
Past online purchase	0.043	0.172*	0.161**	0.229**	0.359***
Past offline purchase	0.015	0.187***	0.127***	0.048	0.057
Purchase from competitors	0.007	0.075	0.056	0.142	0.269*
Age	0.008*	0.003	0.001	0.007*	0.002
Gender	-0.135	0.088	0.042	0.176	-0.113
Recency	-0.018***	-0.007***	-0.007***	-0.012**	-0.008***
Economic recession	-0.065	-0.154**	-0.043	-0.137**	-0.061
Seasonality 1: March	0.308***	0.301***	0.276***	0.341***	0.189***
Seasonality 2: August	-0.062	-0.249***	-0.155**	-0.160*	-0.055
Seasonality 3: April & May	0.150**	-0.018	0.112**	-0.009	0.065
Seasonality 4: June & October	0.131**	0.001	0.049	0.078	0.078*
Constant	-1.599***	-1.431***	-1.503***	-0.986***	-1.442***

***Significant at .001. **Significant at .01. *Significant at .05.

Table A.4: Order Size Model (24 months and full sample)

Variable	Innovator	Early Adopter	Early Majority	Late Majority	Laggard
Postadoption	7.044	-3.233	8.406	-2.745	-0.290
Postadoption × Treated group	-6.745	-2.790	17.602**	4.890	0.481
Last order size	0.071*	0.108***	0.149***	0.142***	0.153***
Age	0.512	0.056	0.066	-0.044	-0.049
Gender	-13.504	6.666	0.372	1.660	-5.222
Recency	-0.087	0.013	-0.426	-0.367	0.120
Economic recession	-0.435	9.839	-14.973***	-21.504***	3.200
Seasonality 1: March	13.650	2.128	10.423	16.121	2.421
Seasonality 2: August	8.722	-3.567	-21.744	-14.390	-5.301
Seasonality 3: April & May	15.135	3.241	-0.502	-8.235	-1.165
Seasonality 4: June & October	9.394	3.381	-3.284	0.537	-1.843
Constant	-10.100	61.620	-104.056	8.924	59.013

***Significant at .001. **Significant at .01. *Significant at .05.

Table B.1: DID Analysis: Late Majority Segment

	Online Adopters			Offline Customers		
	Before	After	Change	Before	After	Change
Laggard						
Total purchase amount	382.92	356.66	-26.26	253.07	261.91	8.83
(in Euros)	(315.58)	(316.00)	(350.91)	(297.75)	(404.73)	(418.71)
Total transactions	4.36	4.32	-0.04	2.95	2.96	0.01
	(3.56)	(3.86)	(3.93)	(3.33)	(3.81)	(3.65)
Offline purchase amount	382.92	273.81	-109.11*			
(in Euros)	(315.58)	(292.41)	(336.03)			
Offline transactions	4.36	3.28	-1.09*			
	(3.56)	(3.47)	(3.63)			

Notes: This table provides the means, with the standard deviations in brackets.
*Significantly different from 0 at least at the 10% level.
#The change in the variable for online adopters is significantly different from the change for offline customers (control group) at least at the 10% level.

Table B.2: Purchase Incidence–Order Size Model: Late Majority Segment (24 months)

Variable	Purchase Incidence	Order Size
Postadoption	-0.081	-0.928
Postadoption × Treated group	0.013	-1.316
Past online purchase	0.151	--
Past offline purchase	0.031	--
Purchase from competitors	0.325**	--
Last order size	--	0.164***
Age	0.005	-0.398*
Gender	0.159	-3.379
Recency	-0.022***	-0.094
Economic recession	-0.037	-4.550
Seasonality 1: March	0.343***	11.893
Seasonality 2: August	-0.080	-0.453
Seasonality 3: April & May	-0.024	-5.576
Seasonality 4: June & October	0.098*	-0.072
Constant	-0.985***	65.756

***Significant at .001. **Significant at .01. *Significant at .05.

Table C.1: Summary of Items

Scale	Item	Source
Satisfaction	Overall I am satisfied with this brand. As a regular customer, I have a high-quality relationship with this brand. I am happy with the efforts the brand is making towards regular customers like me. I am satisfied with the relationship I have with this brand.	Adapted from De Wulf et al. (2001) and Dubé & Morgan (1996)
Shopping enjoyment	I like shopping. I take my time when I do shopping.	Konus et al. (2008)
Time pressure	I am always busy. I usually find myself pressed for time.	Konus et al. (2008)
Price consciousness	It is important for me to have the best price for the product. I compare the prices of products before I make a choice. I like to search carefully before buying products or services.	Adapted from Konus et al. (2008) and Lichtenstein et al. (1990)

Table C.2: Results of Principle Component Analysis: Eigenvalue

Factor Number	Supermarket	Banking	Healthcare
1	4.105	3.907	3.684
2	2.281	2.725	2.876
3	1.631	1.627	1.635
4	1.141	1.135	1.146
5	0.450	0.448	0.448
6	0.298	0.282	0.286
7	0.290	0.239	0.248
8	0.244	0.221	0.221
9	0.224	0.173	0.220
10	0.199	0.145	0.140
11	0.136	0.098	0.096

Table C.3: Result of Principle Component Analysis: Rotated Component Matrix

	Supermarket				Banking				Healthcare			
	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
Post-satisfaction												
Item 1	0.875	0.060	0.054	0.111	0.939	0.044	0.069	0.036	0.913	0.024	0.066	0.031
Item 2	0.899	0.074	0.046	0.079	0.932	0.008	0.040	0.040	0.942	0.026	-0.001	-0.006
Item 3	0.926	0.073	0.081	0.063	0.949	0.045	0.070	0.034	0.948	0.052	0.030	0.007
Item 4	0.914	0.115	0.080	0.065	0.948	0.038	0.079	0.027	0.943	0.042	0.004	0.010
Shopping enjoyment												
Item 1	0.080	0.063	0.897	0.102	0.066	0.068	0.898	0.105	-0.006	0.069	0.900	0.105
Item 2	0.083	0.160	0.904	-0.030	0.103	0.164	0.901	-0.029	0.057	0.161	0.906	-0.026
Time pressure												
Item 1	0.123	0.151	0.095	0.911	0.073	0.156	0.095	0.916	0.040	0.155	0.099	0.919
Item 2	0.105	0.165	-0.010	0.918	0.022	0.170	-0.006	0.923	-0.010	0.172	-0.006	0.923
Price consciousness												
Item 1	0.092	0.663	0.506	0.057	0.068	0.667	0.504	0.059	0.075	0.662	0.509	0.062
Item 2	0.067	0.859	0.041	0.244	0.023	0.861	0.040	0.244	0.023	0.862	0.042	0.244
Item 3	0.131	0.916	0.084	0.092	0.036	0.923	0.087	0.100	0.046	0.922	0.091	0.101

Table C.4: Correlation Matrix of Satisfaction Model in the Supermarket Category

	1	2	3	4	5	6	7	8	9	10	11	12
1. Vol. Store transaction	1.000											
2. Vol. TV & newspaper	0.052	1.000										
3. Vol. Billboard	0.065	0.160	1.000									
4. Vol. Direct communication	0.109	0.263	0.043	1.000								
5. Vol. Online banner	0.040	0.197	0.016	0.193	1.000							
6. Vol. In-store communication	0.220	0.238	0.118	0.199	0.038	1.000						
7. Vol. Publicity	0.050	0.748	0.133	0.133	0.061	0.175	1.000					
8. Vol. WOM from friends	0.114	0.143	0.253	0.163	0.025	0.018	0.159	1.000				
9. Val. Store transaction	0.132	-0.083	-0.106	-0.007	0.002	0.073	-0.042	-0.031	1.000			
10. Val. TV & newspaper	-0.093	0.173	0.094	0.090	0.148	0.037	0.076	0.064	0.152	1.000		
11. Val. Billboard	-0.060	0.063	0.457	0.065	0.067	0.176	0.038	0.039	-0.017	0.242	1.000	
12. Val. Direct communication	0.033	0.164	0.037	0.438	0.187	0.068	0.143	0.176	0.103	0.262	0.091	1.000
13. Val. Online banner	0.020	0.240	0.067	0.188	0.502	0.070	0.177	0.044	0.069	0.258	0.144	0.246
14. Val. In-store communication	0.140	0.071	0.082	0.051	-0.036	0.489	0.055	0.054	0.326	0.123	0.161	0.120
15. Val. Publicity	-0.036	0.036	0.168	-0.027	0.009	0.082	0.108	0.019	0.103	0.090	0.158	-0.033
16. Val. WOM from friends	0.079	0.049	0.011	0.085	-0.025	-0.043	0.008	0.481	0.064	0.221	0.032	0.214
17. Pre-satisfaction	-0.012	0.064	0.004	0.016	0.012	0.093	0.065	0.017	0.286	0.280	0.111	0.145
18. Age	0.129	0.151	-0.004	-0.004	0.053	0.036	0.122	-0.012	0.025	-0.063	0.001	-0.022
19. Gender	0.071	-0.027	-0.071	-0.050	-0.122	0.002	0.025	-0.065	-0.124	-0.059	-0.091	-0.039
20. Social status	0.025	-0.021	-0.054	0.033	-0.047	0.010	0.051	0.006	0.024	-0.048	0.052	0.020
21. Education	-0.022	-0.066	0.051	-0.055	-0.031	-0.021	-0.058	-0.008	-0.047	-0.011	0.022	-0.037
22. Shopping enjoyment	-0.060	0.118	0.075	0.090	0.104	0.083	0.077	0.052	0.038	0.151	0.071	0.089
23. Time pressure	-0.012	-0.013	0.082	-0.016	0.047	0.030	-0.039	-0.078	0.084	0.000	0.136	-0.003
24. Price consciousness	0.014	0.063	0.039	0.031	0.070	0.000	0.078	0.009	0.070	0.156	0.106	0.120
	13	14	15	16	17	18	19	20	21	22	23	24
13. Val. Online banner	1.000											
14. Val. In-store communication	0.024	1.000										
15. Val. Publicity	0.115	0.074	1.000									
16. Val. WOM from friends	-0.013	0.081	0.028	1.000								
17. Pre-satisfaction	0.075	0.240	0.060	0.136	1.000							
18. Age	0.018	0.037	0.055	0.044	-0.064	1.000						
19. Gender	-0.131	-0.112	-0.033	0.020	-0.055	0.049	1.000					
20. Social status	0.036	-0.026	-0.082	-0.017	-0.098	-0.086	-0.001	1.000				
21. Education	-0.035	-0.154	-0.065	-0.061	0.013	-0.135	-0.008	0.253	1.000			
22. Shopping enjoyment	0.084	0.109	-0.044	0.064	0.202	-0.091	-0.187	-0.132	-0.111	1.000		
23. Time pressure	0.030	0.035	0.063	-0.053	0.163	-0.086	-0.130	-0.004	0.132	0.124	1.000	
24. Price consciousness	0.036	0.031	0.006	0.048	0.182	0.030	0.027	-0.043	0.009	0.375	0.312	1.000

Table C.5: Correlation Matrix of Satisfaction Model in the Banking Category

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Vol. Store transaction	1.000												
2. Vol. Online transaction	0.055	1.000											
3. Vol. TV & newspaper	0.013	0.026	1.000										
4. Vol. Billboard	-0.025	-0.058	0.294	1.000									
5. Vol. Direct communication	0.056	0.090	0.022	0.092	1.000								
6. Vol. Online banner	0.018	0.027	0.292	0.025	0.031	1.000							
7. Vol. In-store communication	0.128	0.044	0.038	0.019	0.019	0.083	1.000						
8. Vol. Publicity	0.047	-0.009	0.612	0.011	-0.017	0.243	0.010	1.000					
9. Vol. WOM from friends	0.009	-0.079	-0.025	0.012	0.022	-0.025	0.032	0.056	1.000				
10. Val. Store transaction	0.343	0.086	-0.077	-0.100	0.020	0.010	-0.045	0.006	-0.086	1.000			
11. Val. Online transaction	-0.015	0.342	-0.090	-0.070	0.041	0.050	-0.027	-0.020	-0.008	0.170	1.000		
12. Val. TV & newspaper	-0.135	0.015	0.188	0.075	-0.064	0.032	0.013	-0.003	-0.024	0.096	0.179	1.000	
13. Val. Billboard	0.009	-0.021	0.147	0.373	-0.047	0.018	0.096	0.033	-0.002	0.033	0.061	0.328	1.000
14. Val. Direct communication	-0.023	0.113	-0.087	0.000	0.247	0.010	-0.035	-0.064	-0.047	0.250	0.202	0.214	0.173
15. Val. Online banner	-0.011	0.016	0.061	-0.074	-0.011	0.381	0.038	0.055	-0.018	0.092	0.177	0.256	0.072
16. Val. In-store communication	0.010	-0.014	0.086	0.032	-0.030	0.067	0.494	-0.017	-0.116	0.003	0.013	0.170	0.100
17. Val. Publicity	-0.028	-0.117	-0.078	-0.026	0.011	0.005	0.075	-0.100	0.155	0.096	0.046	0.248	0.132
18. Val. WOM from friends	-0.041	0.019	0.018	0.079	-0.064	-0.013	-0.032	0.076	-0.084	0.052	0.079	0.135	0.191
19. Pre-satisfaction	0.068	-0.080	-0.083	-0.020	0.050	-0.028	-0.025	-0.085	-0.025	0.252	0.186	0.391	0.144
20. Age	0.151	0.085	0.072	0.007	0.075	-0.058	-0.044	0.171	0.026	0.082	-0.002	-0.069	-0.036
21. Gender	-0.011	0.032	-0.047	0.001	-0.057	-0.077	0.000	0.030	-0.051	-0.053	-0.049	-0.068	-0.094
22. Social status	-0.067	0.039	0.001	-0.003	0.137	0.017	0.015	0.052	0.062	-0.090	-0.020	-0.005	0.009
23. Education	-0.111	0.072	0.045	0.020	0.071	0.036	0.062	-0.100	-0.027	-0.100	0.000	-0.020	-0.033
24. Shopping enjoyment	0.014	-0.161	0.059	-0.017	0.003	0.077	0.089	0.088	0.022	0.090	0.040	0.149	0.097
25. Time pressure	-0.062	-0.172	-0.046	0.082	-0.008	-0.085	0.040	-0.071	0.062	0.018	0.010	0.048	0.095
26. Price consciousness	-0.009	-0.020	0.070	-0.005	-0.059	0.028	0.086	0.094	-0.023	0.082	0.105	0.176	0.079

	14	15	16	17	18	19	20	21	22	23	24	25	26
14. Val. Direct communication	1.000												
15. Val. Online banner	0.145	1.000											
16. Val. In-store communication	0.032	0.140	1.000										
17. Val. Publicity	0.195	0.060	0.153	1.000									
18. Val. WOM from friends	0.090	0.026	0.033	0.207	1.000								
19. Pre-satisfaction	0.316	0.162	0.096	0.221	0.100	1.000							
20. Age	-0.032	0.041	-0.044	0.003	0.069	-0.021	1.000						
21. Gender	-0.083	-0.156	0.032	0.025	-0.030	0.002	0.085	1.000					
22. Social status	0.015	-0.081	-0.103	0.016	-0.011	-0.033	-0.099	0.014	1.000				
23. Education	-0.024	-0.066	0.001	0.015	-0.040	-0.050	-0.086	0.019	0.210	1.000			
24. Shopping enjoyment	0.116	0.145	0.134	0.108	0.083	0.190	-0.076	-0.161	-0.138	-0.132	1.000		
25. Time pressure	-0.046	-0.077	0.030	0.103	-0.055	0.104	-0.095	-0.093	0.005	0.128	0.088	1.000	
26. Price consciousness	0.087	0.052	0.141	0.038	-0.089	0.113	0.054	0.040	-0.064	0.019	0.375	0.286	1.000

Table C.6: Correlation Matrix of Satisfaction Model in the Healthcare Category

	1	2	3	4	5	6	7	8	9	10	11
1. Vol. Store transaction	1.000										
2. Vol. TV & newspaper	-0.121	1.000									
3. Vol. Billboard	0.021	0.159	1.000								
4. Vol. Direct communication	-0.027	0.164	-0.019	1.000							
5. Vol. In-store communication	0.000	0.053	0.204	-0.010	1.000						
6. Vol. Publicity	-0.072	0.082	0.283	0.009	0.005	1.000					
7. Vol. WOM from friends	0.047	-0.005	-0.053	0.059	-0.037	0.141	1.000				
8. Val. Store transaction	0.419	-0.011	0.073	0.010	0.062	0.011	0.033	1.000			
9. Val. TV & Newspaper	-0.161	0.438	0.137	-0.021	0.109	0.055	-0.116	-0.126	1.000		
10. Val. Billboard	-0.059	0.231	0.462	-0.002	0.257	0.105	0.020	0.068	0.263	1.000	
11. Val. Direct communication	0.026	0.104	-0.022	0.561	0.014	0.040	0.110	0.119	0.046	0.036	1.000
12. Val. In-store communication	-0.130	0.133	0.229	0.033	0.506	0.092	0.035	-0.009	0.237	0.278	0.076
13. Val. Publicity	0.169	-0.010	0.049	0.021	-0.075	-0.088	-0.084	0.162	0.082	0.097	0.079
14. Val. WOM from friends	-0.050	-0.006	-0.099	0.092	-0.017	-0.140	0.039	0.060	-0.025	-0.001	0.230
15. Pre-satisfaction	0.089	0.004	0.050	0.064	-0.004	-0.029	-0.098	0.261	0.045	0.128	0.225
16. Age	0.059	-0.062	0.114	0.039	-0.068	0.217	0.030	0.181	-0.019	-0.029	0.118
17. Gender	-0.112	0.003	0.003	-0.057	-0.056	-0.036	-0.106	-0.065	0.067	0.034	0.028
18. Social status	-0.104	0.084	-0.113	0.090	0.065	0.042	-0.029	-0.133	-0.046	-0.104	0.076
19. Education	0.070	0.070	0.039	-0.063	0.029	-0.086	-0.033	-0.082	0.061	0.078	-0.066
20. Shopping enjoyment	0.008	0.068	0.043	0.060	0.105	0.025	0.121	-0.048	0.199	-0.015	0.034
21. Time pressure	0.072	-0.017	0.076	-0.003	0.133	-0.040	0.038	-0.037	0.107	0.126	0.076
22. Price consciousness	0.024	-0.059	0.029	0.024	0.102	0.099	0.094	-0.064	0.085	-0.054	0.098

	12	13	14	15	16	17	18	19	20	21	22
12. Val. In-store communication	1.000										
13. Val. Publicity	0.045	1.000									
14. Val. WOM from friends	-0.047	0.176	1.000								
15. Pre-satisfaction	-0.051	0.179	0.272	1.000							
16. Age	-0.121	0.083	0.115	0.158	1.000						
17. Gender	-0.020	0.006	0.158	0.120	0.115	1.000					
18. Social status	0.052	-0.088	0.041	-0.152	-0.113	-0.030	1.000				
19. Education	0.026	-0.163	0.027	-0.033	-0.155	0.066	0.255	1.000			
20. Shopping enjoyment	0.070	0.117	0.050	-0.013	-0.116	-0.136	-0.142	-0.179	1.000		
21. Time pressure	0.106	-0.014	-0.062	0.019	-0.050	-0.109	0.082	0.191	0.124	1.000	
22. Price consciousness	0.123	0.086	-0.010	0.179	0.088	0.112	-0.015	-0.060	0.393	0.263	1.000

Table C.7: Correlation Matrix of Behavior Model in the Supermarket Category

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. S.D. Store transaction	1.000													
2. Vol. Store transaction	0.286	1.000												
3. Vol. TV & newspaper	0.016	0.106	1.000											
4. Vol. Billboard	0.010	0.072	0.142	1.000										
5. Vol. Direct communication	0.032	0.196	0.243	0.036	1.000									
6. Vol. Online banner	0.009	0.110	0.187	0.040	0.160	1.000								
7. Vol. In-store communication	0.093	0.318	0.276	0.134	0.193	0.042	1.000							
8. Vol. Publicity	0.007	0.067	0.613	0.152	0.131	0.066	0.142	1.000						
9. Vol. WOM from friends	0.047	0.142	0.142	0.185	0.179	0.047	0.028	0.114	1.000					
10. Val. Store transaction	0.100	0.085	0.093	0.024	0.034	0.011	0.018	0.044	0.024	1.000				
11. Val. TV & newspaper	0.036	0.067	0.573	0.043	0.077	0.060	0.066	0.570	0.160	0.167	1.000			
12. Val. Billboard	0.062	0.096	0.064	0.050	0.014	-0.017	0.101	0.067	0.113	0.120	0.289	1.000		
13. Val. Direct communication	0.040	0.133	0.027	0.022	0.183	0.010	0.150	0.025	0.216	0.022	0.173	0.044	1.000	
14. Val. Online banner	0.017	0.058	0.064	-0.005	0.050	0.223	0.071	0.020	0.160	0.023	0.114	-0.007	0.399	1.000
15. Val. In-store communicatior	0.003	-0.019	0.056	0.019	0.031	-0.013	0.131	0.084	0.011	0.145	0.083	0.028	0.030	0.041
16. Val. Publicity	0.035	0.055	0.518	0.027	0.067	0.017	0.061	0.414	0.057	0.233	0.488	0.125	-0.014	-0.011
17. Val. WOM from friends	0.014	0.072	0.123	0.280	0.011	0.036	0.040	0.173	0.437	0.029	0.135	-0.005	0.075	-0.006
18. Pre-satisfaction	-0.005	0.044	0.056	0.020	-0.008	0.017	0.116	0.070	-0.004	-0.223	-0.010	-0.036	-0.025	-0.032
19. Time trend	0.007	0.483	0.217	0.129	0.203	0.130	0.222	0.131	0.127	0.191	0.098	0.040	0.058	0.042
20. Weekend	0.035	-0.049	-0.019	-0.016	-0.010	-0.009	-0.023	-0.010	-0.013	-0.019	-0.006	-0.004	0.004	-0.004
21. Age	0.034	0.061	0.101	-0.015	-0.017	0.047	0.000	0.086	-0.010	0.017	0.108	0.070	0.010	-0.008
22. Gender	0.020	0.026	-0.032	-0.064	-0.043	-0.101	-0.044	-0.014	-0.013	0.113	0.015	0.048	-0.023	-0.039
23. Social status	0.012	0.037	-0.041	-0.058	0.036	-0.040	0.014	0.019	0.007	0.017	0.058	0.035	0.053	-0.043
24. Education	-0.004	0.004	-0.051	0.049	-0.039	-0.021	-0.020	-0.037	-0.007	-0.021	-0.036	-0.051	0.005	-0.004
25. Shopping enjoyment	-0.018	-0.041	0.088	0.063	0.085	0.088	0.113	0.048	0.017	-0.020	0.082	0.021	-0.006	0.033
26. Time pressure	-0.001	0.029	-0.010	0.089	-0.002	0.033	0.026	0.000	-0.066	-0.059	-0.007	-0.099	0.005	-0.008
27. Price consciousness	0.008	0.009	0.046	0.041	0.037	0.065	0.025	0.025	-0.002	-0.009	0.035	0.012	-0.057	-0.039

	15	16	17	18	19	20	21	22	23	24	25	26	27
15. Val. In-store communicatior	1.000												
16. Val. Publicity	0.072	1.000											
17. Val. WOM from friends	0.010	0.066	1.000										
18. Pre-satisfaction	-0.063	-0.025	-0.004	1.000									
19. Time trend	0.071	0.079	0.047	0.000	1.000								
20. Weekend	-0.004	-0.006	-0.004	-0.001	-0.101	1.000							
21. Age	0.003	0.064	-0.038	-0.064	0.000	0.002	1.000						
22. Gender	0.061	0.061	-0.050	-0.055	0.000	0.002	0.049	1.000					
23. Social status	0.019	0.055	-0.003	-0.098	0.000	0.001	-0.086	-0.001	1.000				
24. Education	0.052	-0.043	0.020	0.013	0.000	0.000	-0.135	-0.008	0.253	1.000			
25. Shopping enjoyment	-0.054	0.048	-0.019	0.202	0.000	-0.001	-0.091	-0.187	-0.132	-0.111	1.000		
26. Time pressure	0.001	-0.066	-0.012	0.163	0.000	0.000	-0.086	-0.130	-0.004	0.132	0.124	1.000	
27. Price consciousness	-0.031	0.082	-0.004	0.182	0.000	-0.001	0.030	0.027	-0.043	0.009	0.375	0.312	1.000

Table C.8: Correlation Matrix of Behavior Model in the Banking Category

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. S.D. Store transaction	1.000														
2. S.D. Online transaction	-0.007	1.000													
3. Vol. Store transaction	0.333	0.026	1.000												
4. Vol. Online transaction	0.015	0.417	0.095	1.000											
5. Vol. TV & newspaper	-0.005	0.002	0.047	0.072	1.000										
6. Vol. Billboard	0.006	-0.024	0.018	-0.022	0.327	1.000									
7. Vol. Direct communication	0.001	0.030	0.094	0.155	0.045	0.065	1.000								
8. Vol. Online banner	0.018	0.005	0.048	0.061	0.251	0.021	0.048	1.000							
9. Vol. In-store communication	0.032	0.006	0.094	0.037	0.072	0.061	0.046	0.155	1.000						
10. Vol. Publicity	0.032	-0.013	0.084	-0.017	0.522	0.031	0.010	0.193	0.065	1.000					
11. Vol. WOM from friends	-0.006	-0.028	0.017	-0.034	0.026	0.014	-0.023	0.049	0.029	0.193	1.000				
12. Val. Store transaction	0.115	-0.033	0.079	-0.044	-0.034	0.000	0.023	0.017	0.065	-0.002	-0.041	1.000			
13. Val. Online transaction	0.022	0.077	0.108	0.066	-0.010	-0.026	-0.031	0.053	0.042	-0.016	0.014	0.082	1.000		
14. Val. TV & newspaper	0.038	-0.017	0.107	-0.010	0.132	0.034	-0.007	0.074	0.000	0.160	-0.035	0.195	0.011	1.000	
15. Val. Billboard	-0.004	-0.021	-0.039	-0.037	-0.005	0.119	-0.002	0.009	-0.024	-0.005	-0.020	0.112	-0.029	0.296	1.000
16. Val. Direct communication	0.002	-0.012	0.040	-0.009	-0.014	-0.027	0.048	0.000	0.033	-0.007	-0.019	0.206	0.068	0.384	0.302
17. Val. Online banner	-0.011	-0.008	-0.022	-0.022	0.104	-0.007	-0.043	0.079	-0.020	0.206	-0.026	0.058	0.200	0.213	0.088
18. Val. In-store communication	0.018	-0.019	0.016	-0.026	-0.028	0.004	0.003	-0.019	-0.015	-0.011	-0.013	0.171	-0.018	0.013	-0.008
19. Val. Publicity	0.013	0.004	0.052	0.042	0.494	0.006	-0.039	0.144	-0.014	0.598	-0.008	0.044	0.002	0.254	0.025
20. Val. WOM from friends	0.006	-0.023	0.005	-0.041	-0.012	-0.022	0.026	-0.007	-0.023	-0.005	-0.020	0.021	-0.028	0.045	0.057
21. Pre-satisfaction	0.025	-0.034	0.078	-0.024	0.011	0.008	0.131	0.000	0.018	-0.038	-0.002	-0.125	-0.127	-0.181	-0.114
22. Time trend	0.005	-0.033	0.230	0.257	0.238	0.112	0.233	0.132	0.096	0.095	0.092	0.144	0.127	0.119	0.058
23. Weekend	0.015	-0.001	-0.017	-0.024	-0.028	-0.010	-0.016	-0.013	-0.008	-0.010	-0.013	-0.014	-0.013	-0.014	-0.002
24. Age	0.051	0.039	0.124	0.052	0.002	-0.011	-0.007	-0.054	-0.027	0.131	0.009	0.049	-0.030	0.106	0.018
25. Gender	-0.003	0.015	-0.001	0.036	-0.071	-0.012	-0.031	-0.087	-0.021	0.039	-0.091	0.061	-0.041	0.035	0.083
26. Social status	-0.020	0.017	-0.050	0.016	0.010	-0.056	0.103	-0.001	-0.005	0.019	-0.007	-0.008	0.040	-0.002	0.067
27. Education	-0.037	0.033	-0.092	0.038	0.017	-0.004	0.019	0.027	0.063	-0.076	-0.008	0.037	0.089	0.032	0.077
28. Shopping enjoyment	0.004	-0.072	0.032	-0.119	0.043	0.016	0.049	0.086	0.109	0.081	0.034	-0.049	-0.068	-0.029	-0.097
29. Time pressure	-0.022	-0.075	-0.070	-0.125	-0.003	0.076	0.014	-0.058	0.070	-0.024	-0.022	0.014	0.022	-0.062	0.001
30. Price consciousness	-0.003	-0.006	-0.005	-0.009	0.051	0.014	-0.013	0.032	0.092	0.086	-0.051	-0.053	0.003	-0.039	-0.072

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
16. Val. Direct communication	1.000														
17. Val. Online banner	0.118	1.000													
18. Val. In-store communication	-0.007	-0.011	1.000												
19. Val. Publicity	0.028	0.129	0.151	1.000											
20. Val. WOM from friends	0.110	-0.017	0.066	0.002	1.000										
21. Pre-satisfaction	-0.139	-0.073	-0.063	-0.076	-0.051	1.000									
22. Time trend	0.158	0.072	0.043	0.103	0.057	0.000	1.000								
23. Weekend	-0.012	-0.004	-0.005	-0.013	-0.008	0.001	-0.104	1.000							
24. Age	0.067	-0.061	0.047	0.104	0.002	-0.021	0.000	0.003	1.000						
25. Gender	-0.002	0.097	-0.020	0.024	0.029	0.002	0.000	0.001	0.085	1.000					
26. Social status	0.032	0.020	-0.044	0.039	0.065	-0.033	0.000	0.000	-0.099	0.014	1.000				
27. Education	0.084	0.043	-0.008	-0.086	-0.033	-0.050	0.000	0.000	-0.086	0.019	0.210	1.000			
28. Shopping enjoyment	-0.067	0.002	0.033	0.055	-0.010	0.190	0.000	-0.001	-0.076	-0.161	-0.138	-0.132	1.000		
29. Time pressure	-0.010	-0.040	-0.084	-0.081	0.096	0.104	0.000	-0.001	-0.095	-0.093	0.005	0.128	0.088	1.000	
30. Price consciousness	-0.065	0.035	-0.025	0.075	0.029	0.113	0.000	0.001	0.054	0.040	-0.064	0.019	0.375	0.286	1.000

Table C.9: Correlation Matrix of Behavior Model in the Healthcare Category

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. S.D. Store transaction	1.000												
2. Vol. Store transaction	0.247	1.000											
3. Vol. TV & newspaper	-0.024	-0.053	1.000										
4. Vol. Billboard	0.012	0.089	0.136	1.000									
5. Vol. Direct communicati	0.013	0.071	0.134	0.000	1.000								
6. Vol. In-store communicat	0.001	0.051	0.094	0.256	0.029	1.000							
7. Vol. Publicity	-0.004	0.051	0.062	0.259	0.091	0.015	1.000						
8. Vol. WOM from friends	-0.005	0.122	-0.029	-0.015	0.096	-0.012	0.085	1.000					
9. Val. Store transaction	0.102	0.129	-0.046	-0.051	0.043	-0.040	0.128	-0.047	1.000				
10. Val. TV & Newspaper	0.020	0.059	0.041	-0.029	0.092	-0.024	0.019	0.061	-0.039	1.000			
11. Val. Billboard	0.001	0.111	0.005	-0.011	0.017	-0.016	-0.034	-0.026	-0.026	0.125	1.000		
12. Val. Direct communicat	-0.006	-0.061	-0.037	-0.031	-0.003	-0.024	-0.051	-0.040	0.019	0.123	-0.016	1.000	
13. Val. In-store communica	0.014	0.059	-0.024	-0.020	-0.036	-0.016	0.004	-0.026	0.236	-0.015	-0.010	-0.016	1.000
14. Val. Publicity	-0.029	-0.059	0.029	0.211	-0.014	-0.014	0.634	0.053	0.062	0.069	-0.022	-0.004	-0.028
15. Val. WOM from friends	0.016	0.036	-0.021	-0.021	-0.002	-0.019	0.123	0.206	0.171	0.040	-0.025	0.068	-0.025
16. Pre-satisfaction	0.016	0.073	0.023	0.049	0.105	0.004	-0.010	0.019	-0.037	-0.049	-0.051	-0.078	0.043
17. Time trend	0.007	0.380	0.144	0.120	0.203	0.075	0.191	0.163	0.129	0.069	0.036	0.121	0.031
18. Weekend	-0.032	-0.031	-0.007	-0.012	-0.015	-0.006	-0.026	-0.014	-0.017	-0.013	-0.009	-0.005	-0.002
19. Age	0.009	0.062	-0.079	0.086	0.049	-0.085	0.142	0.001	0.022	0.033	-0.002	-0.103	0.004
20. Gender	-0.030	-0.037	0.040	-0.043	-0.081	-0.044	-0.010	-0.004	-0.027	0.024	0.000	0.000	0.024
21. Social status	-0.020	-0.098	0.012	-0.130	0.075	0.052	0.025	-0.028	0.001	0.093	0.062	0.054	0.062
22. Education	0.013	0.001	0.073	0.026	-0.073	0.030	-0.089	-0.032	0.077	0.028	-0.039	0.000	0.007
23. Shopping enjoyment	-0.001	-0.019	0.071	0.033	0.098	0.092	0.058	0.106	0.075	-0.026	0.086	-0.004	0.013
24. Time pressure	0.020	0.034	0.023	0.079	0.036	0.119	-0.054	0.013	0.073	-0.107	-0.001	-0.025	-0.043
25. Price consciousness	0.004	-0.008	-0.006	0.028	0.051	0.101	0.095	0.072	0.068	-0.089	0.076	-0.065	-0.056

	14	15	16	17	18	19	20	21	22	23	24	25
14. Val. Publicity	1.000											
15. Val. WOM from friends	0.191	1.000										
16. Pre-satisfaction	-0.054	-0.217	1.000									
17. Time trend	0.211	0.142	0.000	1.000								
18. Weekend	-0.026	-0.009	0.002	-0.102	1.000							
19. Age	0.105	-0.047	0.158	0.000	0.002	1.000						
20. Gender	-0.031	-0.127	0.120	0.000	0.002	0.115	1.000					
21. Social status	0.055	-0.029	-0.152	0.000	0.000	-0.113	-0.030	1.000				
22. Education	-0.010	0.024	-0.033	0.000	0.000	-0.155	0.066	0.255	1.000			
23. Shopping enjoyment	0.022	0.064	-0.013	0.000	-0.002	-0.116	-0.136	-0.142	-0.179	1.000		
24. Time pressure	-0.034	0.128	0.019	0.000	-0.001	-0.050	-0.109	0.082	0.191	0.124	1.000	
25. Price consciousness	0.037	0.076	0.179	0.000	0.000	0.088	0.112	-0.015	-0.060	0.393	0.263	1.000

Summary

Customers increasingly use various channels and touchpoints to browse products or search information, purchase, and obtain after-sales services, such as the brick-and-mortar stores, catalogs, online channels, mobile devices, mass media, word-of-mouths etc. The proliferation of online shopping and touchpoint multiplicity generate opportunities as well as great challenges for firms to manage effectively across the multiple channels and touchpoints. This dissertation thus pursues to gain a deep understanding of the multichannel, multi-touchpoint customer behavior and experience, and aims to provide insights for firms to successfully introduce new channels and manage customer experience in the multi-channel environment. Specifically, the dissertation: (i) compares customer purchase amount and investigates the effects of new online channel adoption on purchase volumes across different segments; (ii) investigates the effects of cross-channel competition on channel migration and firm purchase volume and (iii) explores the influence of instant and holistic customer experience with multiple touchpoints on customer satisfaction and behavior. Three studies are conducted to serve the research objective.

Study 1: The Hare and the Tortoise: Do Earlier Online Channel Adopters Purchase More?

Depending on the duration of innovation adoption, innovation diffusion theory classifies customers into five groups: innovator, early adopter, early majority, late majority, and laggard. An empirical generalization reveals that earlier adopter segments of a new product or service tend to be more valuable than later adopter segments; however, it is unknown whether earlier adopters of a new online transactional channel purchase more than later adopters before and after their adoption of the new channel. Study 1 thus segments customers on the basis of purchase amount before adoption and adoption duration, and examines the effects

of their online channel adoption on purchase volumes across the identified segments. The study uses customer transaction data covering 3,270 customers and their 12.5-year daily purchase history from a multichannel French retailer selling natural healthy products. A systematic modelling methodology is employed, consisting by latent class cluster analysis, propensity score matching approach, difference-in-difference analysis, and Type II Tobit model.

The findings of study 1 reveals that the late majority segment purchases more than the other segments, both before and after the adoption of a new online channel. Innovators generate less revenue than the late majority, but more than the rest of segments. Therefore, to target heavy shoppers, managers should not focus only on earliest channel adopters (e.g., innovators), but more importantly, they should consider the late majority segment who adopts during the middle-late period. Furthermore, the effects of online channel adoption on purchase volumes vary between two types of segments: heavy shopper segments (late majority and innovators) and light shopper segments (early adopter, early majority, and laggard). This study shows that the online channel adoption have no effects on the overall purchase volumes of the heavy shopper segments, but enhance the overall purchase volumes of the light shopper segments without cannibalizing the volumes from the existing offline channels. Although both intrinsic benefits and marketing communications drive multichannel customer shopping behavior, these findings support the predominant influence of the benefits of online shopping on customer purchases after they adopt online channels. The varying customers' responses to the new online channel suggest retailers differentiating their strategies to appeal to the two specific groups.

Study 2: Customer Channel Migration in the Competitive Environment: the Effects of Cross-Channel Competition

Customers' previous channel usage influence their current channel choice. However, it remains unknown how customers' previous purchases from competitors' channels affect their adoption of a new online channel and channel migration, and whether customers perceive the same channel different from the focal firm to competitors. Moreover, no study uncovers the effect of online channel adoption on the purchases from competitors at the individual level. To fill these research gaps, study 2 investigates the effects of customers' previous purchases from competitors' channels on customer channel migration, and the effects of online channel adoption and use on purchase volumes of competitors and the focal firm that introduces the new online channel. Study 2 also distinguishes a firm's new and existing customers and investigates the moderate effect of the group type on customer channel migration. This study integrates customer transaction data from ten French multichannel retailers competing in the same home décor category. The data cover eight-year daily purchase history of 20,570 customers. Study 2 employs multivariate probit model with sample selection and Type II Tobit model to test series of hypotheses.

The findings of study 2 shows that the customers who purchase more frequently from competitors' online channels (higher preference to competitors' online channels) before the new online channel introduction are more likely to adopt and purchase from the new online channel. Therefore, the focal firm that introduce its online channel later than competitors may benefit from competitors' online channels. But customers do not always follow their past channel state dependence when switching from competitors to the focal firm; if a customer purchased from competitors' offline channels in the last month, the customer is more likely to choose the new online channel when purchasing with the focal firm. Moreover, compared to new customers, the existing customers are more engaged with the established catalog channel which they are already shopping and less likely to purchase through the new online channel, but their previous purchase experiences with competitors' online channels can greatly promote the chance to purchase from the new online channel. Last but not the least, the adoption and use of new online channel reduce purchase frequencies of competitors, but increase purchase frequencies of the focal firm, both for the existing and new customers. These results imply that the firm should introduce its own online channel when its competitors have already done so.

Study 3: How Do Instant Multi-Touchpoint Experiences Affect Customer Satisfaction and Behavior? A Real-Time Experience Tracking Approach

A customer's brand experience encompasses the holistic experiences with all direct and indirect contact with the brand during the shopping journey. But, no studies can trace the instant customer experiences with the multiple touchpoints during the shopping journey and link these experiences to customer attitude and behavior. Therefore, study 3 investigates the effects of real-time customer experiences with multiple touchpoints on customer satisfaction and customer transaction (incl. product purchase and service usage). This study conducts an innovative, real-time experience tracking approach to collect customer experience data. An initial sample of 448 customers reported their touchpoint experiences via a mobile text message, every time they encountered their main current brand from each of three categories (supermarkets, banking, and healthcare) in a four-week period. This approach collected more than 8,000 encounters from ten touchpoints, classified into customer-initiated touchpoints (incl. online transaction and offline transaction), firm-initiated touchpoints (incl. television and newspaper, billboard, direct communication, online banner and in-store communication), and other-initiated touchpoints (incl. publicity and offline WOM). Study 3 employs dynamic univariate/bivariate probit and linear regression to test models.

The findings of study 3 reveal that customer satisfaction is mostly affected by the valences of touchpoints rather than their volumes. The valence of the customer-initiated touchpoints of store transactions (CITs) increase satisfaction in all investigated categories; the valence effects of firm-initiated touchpoints (FITs) and other-initiated touchpoints (OITs) on satisfaction vary highly across categories and are mostly not significant. Moreover, both previous positive and negative transaction (CIT) experiences increase the incidence of current transactions in the supermarket category. In addition, previous positive and negative experiences with particular FITs and OITs can occasionally enhance the incidence of current transactions but the results are extremely fragmented across categories. Nevertheless these results provide valuable insights for firms to design touchpoint and category - specific strategies.

Theoretical contributions

This dissertation contributes to theory in several ways. The first contribution is to the research on multichannel and multi-touchpoint customer management. This dissertation investigates the effects of customer heterogeneity on new online channel adoption (study 1), the effects of cross-channel competition on channel migration (study 2), and the impacts of online channel adoption on purchase volumes across segments (study 1) and from competitors (study 2). Therefore, the findings of this dissertation provide valuable insight on the antecedents and consequences of new channel adoption in the multichannel setting. In addition, the dissertation extends the boundary of multichannel customer management by exploring customer experiences and behaviors with various touchpoints, including not only the online and offline channels, but also one-way communications (i.e., mass media) exerted by firms and indirect contacts such as publicity and word-of-mouth (study 3).

The second contribution is to the research on customer experience management. Although recent research emphasizes the importance of creating superior customer experience and its consequences, very few studies empirically link the instant multi-touchpoint experience to customer attitude or behavior. The research from study 3 makes great progress on understanding real-time customer experiences with multiple touchpoints and their influences on customer satisfaction and behavior over time. Moreover, this study makes contributes to the customer experience management by introducing and conducting a new real-time data collection approach that is superior to conventional survey methods in collecting the real-time multi-touchpoint experience data.

The third contribution is to the research on innovation management, particularly in the area of innovation adoption. Study 1 and study 2 investigate the effect of various factors on customer adoption of a new online channel and the consequences of customer new channel adoption. Findings of these studies offer implications on the diffusion of new online channel, which also provides insights on customer adoption of other types of channel innovation, such as mobile channel and social media.

Practical implications

The findings in this dissertation provide several practical implications for managers in developing multichannel and multi-touchpoint customer management strategies, and creating superior customer experience.

First, managers should be fully aware the effects of customer heterogeneity on their shopping behavior and the importance of developing the segment-specific strategies, when they introduce new channels. For example, to target heavy shoppers, managers should not focus solely on earliest adopters (e.g., innovators), but more importantly, they should consider the customers who adopt during the middle-late period (late majority segment). Because heavy shopper segments respond to a new online channel introduction differently from the light shopper segments, marketer should differentiate their strategies between the two kinds of segments. In the former group, retail managers should focus on stimulating their online shopping volumes, whereas for the latter group of customers, retailers should work on improving their perceptions of the benefits of online shopping, instead of pushing them hard to shop online. A firm’s existing and new customers also have distinct responses to the online channel introduction, such that existing customers are more likely to purchase from the firm’s existing offline channels and less likely to migrate to the new online channel. Therefore, managers may use the well-established offline channels to retain their relationship with existing customers and devoting more marketing resources on promoting the online sales from new customers.

Second, the findings of this dissertation also provide special guidance for firms that introduce their new online channels later than many of their competitors. The dissertation suggests that managers should not hesitate to introduce their own online channels when competitors have already done so, because by adopting the new online channel, either their existing or new customers reduces overall purchases from competitors but increase purchases from the firm that introduces the online channel. But a good knowledge on customer preference for competitors' channels (e.g., through survey) could help managers predict customer channel migration after the introduction of a new channel.

Finally, this research offers valuable insights into manage customer experiences across a broad range of touchpoints. In general, managers should invest more assets on touchpoint quality instead of touchpoint quantity to increase customer satisfaction and transactions. But they should also notice that their choice between a touchpoint's quality and quantity could vary across touchpoint types. For example, our findings suggest managers investing more resources on promoting the quality of television and newspaper advertising, and increasing the quantity of billboards. Moreover, managers should be aware that the effects of touchpoint experiences vary greatly across categories.

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About the Author

Jing Li was born in Xinxiang, China, on June 21, 1983. After obtaining a bachelor degree in Communication Engineering at Central South University in China, she completed a master of Management Science and Engineering at Tongji University in China. During her master period, she earned a II level master of E-business and Information Communication at Politecnico di Torino in Italy and studied Marketing at Audencia Ecole de Management in France. In February 2010, Jing started her Ph.D. project in the Innovation, Technology Entrepreneurship & Marketing (ITEM) group of the school of Industrial Engineering at Eindhoven University of Technology (The Netherlands) of which the results are presented in this dissertation. Her work has been published in the *Journal of Retailing* and leading international conference proceedings, such as EMAC (2012, 2013, 2015) and Informs Marketing Science (2012, 2013, 2014).