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Journal of Retailing 91 (2, 2015) 289–308

Journal of Retailing

The Hare and the Tortoise: Do Earlier Adopters of Online Channels Purchase More?

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Abstract

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 multichannel French retailer of natural health products. Contrary to 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.

Keywords: E-commerce; Channels; Segmentation; Online retailing; Customer relationship management; Channel adoption

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, Muller, and Wind 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, Mela, and Neslin 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, Kumar, and Ravishanker 2007; Xue, Hitt, and

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http://dx.doi.org/10.1016/j.jretai.2015.01.001
0022-4359/

Chen 2011); no study has however 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 and thus improve overall profits. 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.

In addition, we investigate 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 (e.g., Ansari, Mela, and Neslin 2008; Campbell and Frei 2009; Gensler, Leeflang, and Skiera 2012). Far less research explores its effects on consumer behaviors 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. 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 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.

Conceptual Development

The two-part conceptual framework of this study in Fig. 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).

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 (Konus, Verhoef, and Neslin 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. Konus, Verhoef, and Neslin (2008) segment customers by channel choices across multiple phases 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 consumers into five groups: innovator, early adopter, early majority, late majority, and laggard. These segments differ in their demographics, psychographics, social class, and lifestyles (Gatignon and Robertson 1985; Rogers 2003). For example, early adopters tend to have higher income and status occupations, more education, a

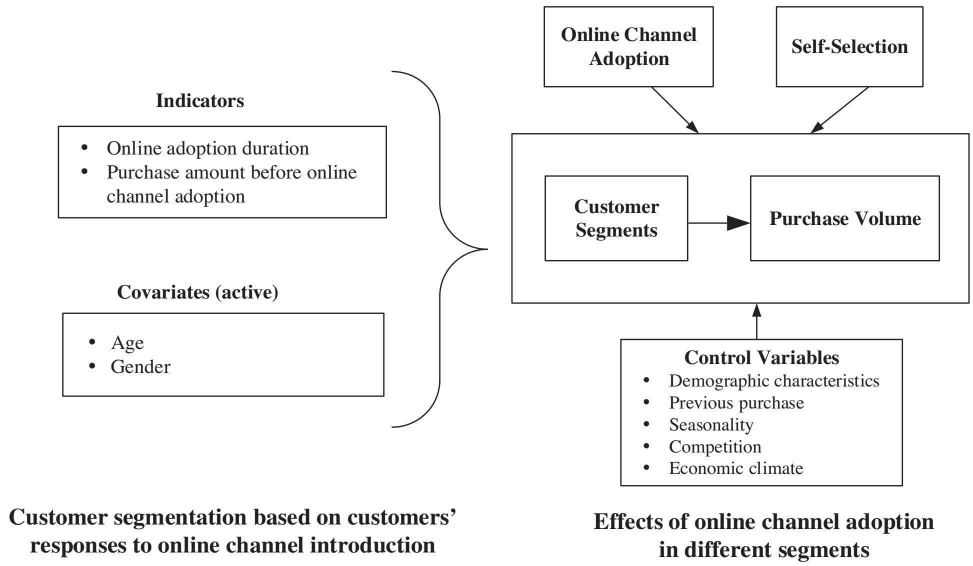

Fig. 1. Conceptual Framework of Online Channel Adoption.

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; Mahajan, Muller, and Srivastava 1990). 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, and Skiera 2012). More transactions 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 channel. Customer expenditures also contribute to behavioral loyalty, which accelerates adoption speed (Demoulin and Zidda 2009). Empirical evidence shows that customers who adopt transactional channels faster also exhibit greater transactional frequency prior to their adoption (Venkatesan, Kumar, and Ravishanker 2007; Xue, Hitt, and Chen 2011). Therefore:

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 channel adoption duration (Venkatesan, Kumar, and Ravishanker 2007; Xue, Hitt, and Chen 2011), and channel choice (Ansari, Mela, and Neslin 2008; Inman, Shankar, and Ferraro 2004). For example, Venkatesan, Kumar, and Ravishanker (2007) find that male customers are more likely to adopt additional channels faster, but their income levels do not affect channel adoption. Xue, Hitt, and Chen (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 (Konus, Verhoef, and Neslin 2008), we do not formulate a formal hypothesis but rather include age and gender as covariates.

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.

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 behaviors 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. Gensler, Leeflang, and Skiera (2012) reveal that the use of online channels increases customer revenue. The research of 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, Mela, and Neslin (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 (e.g., Pauwels et al. 2011). As is well established in marketing, customer heterogeneity critically affects customer responses to a firm's multichannel strategies (e.g., 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, and Skiera 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 (Gensler, Leeflang, and Skiera 2012; Montoya-Weiss, Voss, and Grewal 2003; Wolk and Skiera 2009). Finally, shopping online can 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, Chu, and Cebollada 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, Hitt, and Chen 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, Voss, and Grewal (2003) show that positive perceptions of service quality in an existing channel can inhibit uses of a new online channel. Moreover, according to Konus, Neslin, and Verhoef (2014), heavy shoppers are less affected by changes to its channel repertory (e.g., elimination of a catalog channel), possibly because these customers, who are more familiar with the firm's offerings, perceive fewer changes to their shopping benefits (e.g., search convenience, 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, Mela, and Neslin (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, as 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; 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, Henderson, and Quelch 1985; Zhang, Seetharaman, and Narasimhan 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. Customers with certain characteristics have intrinsic preferences for a particular channel (Boehm 2008; Konus, Verhoef, and Neslin 2008). The differences in characteristics between online adopters and offline customers also exist, such as age, education, and purchase level before online adoption (Hitt and Frei 2002; Neslin et al. 2006; Verhoef and Donkers 2005). 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, and Skiera 2012). Therefore, we employ a matching technique 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, Mela, and Neslin 2008; Xue, Hitt, and Chen 2011). We also consider the effect of previous purchases on current purchases, known as state dependence or inertia (Rust, Lemon, and Zeithaml 2004; Valentini, Montaguti, and Neslin 2011). Because our data span a long period, we control for the impact of time on customer spending, such as seasonality (Ansari, Mela, and Neslin 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, Donkers, and Franses 2009; Verhoef et al. 2009).

Data Description

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 and consulting 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, 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 Fig. 2 details.

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 sample of 1,650 online adopters who adopted the online channel between January 2001–June 2011 and 985 offline only customers.

We provide the demographic descriptions and purchase information (from the focal firm) about the online adopters and offline customers in Table 1. In line with previous studies (e.g., 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.

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 final samples of 1,630 online adopters and 978 offline customers for the modeling.

Model-Free Evidence

We explored the purchase volumes of different customer groups who adopted the online channel at 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 at different times: early adopters (duration ≤40 months), middle-period adopters (40 months < duration ≤80 months), and late adopters (duration >80 months). Table 2 summarizes the average annual purchase amounts for these segments. 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 jump to conclusions from this simple analysis, but the model-free exploration suggests that various shopping patterns emerge among customer groups who adopt online channels at different times.

Methodology

Our methodology consists of three steps and a series of models. We first use latent class cluster analysis (LCCA) to segment customers on the basis of their online adoption duration and

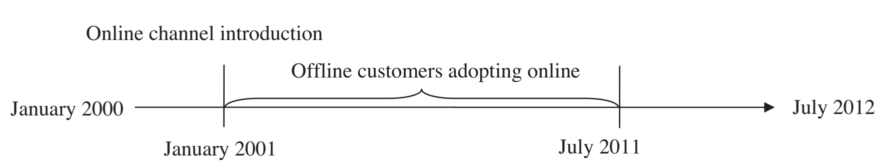

Fig. 2. Timeline and Data Periods.

Table 1
Descriptive statistics for two customer groups.

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

Table 2
Comparison of purchase amounts across adoption periods.

Variable	Adoption duration ≤40 months			40 months < adoption duration ≤80 months			Adoption duration >80 months		
	M	Min	Max	*M*	Min	Max	*M*	Min	Max
Yearly purchase amount	148.1 (125.8)	20.8	1108.8	151.8 (152.4)	13	1623.6	159.2 (188.8)	15.3	2696.5
Yearly purchase amount before adoption	156.4 (134.2)	10.2	853.3	133.1 (130.9)	1	1309.6	145.3 (179.4)	5.9	2196.5
Yearly purchase amount after adoption	147.3 (147.0)	13.2	1482.7	170 (213.1)	12.8	2434.4	200.5 (272.7)	17.1	3807.7

Notes: Values in brackets donate the standardized deviation.

purchase amount before adoption. Next, 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. Fig. 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 modeling purpose.

Latent Class Cluster Analysis (LCCA)

The LCCA segments 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:

$$f(\boldsymbol{y}_i|z_i^{act\_cov}) = \sum_{x=i}^{K} P(x|z_i^{act\_cov}) \coprod_{j=1}^{J} f(y_{ij}|x) \tag{1}$$

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 that is the number of months between online channel introduction and adoption, 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 2005). Furthermore, $z_i^{act\_cov}$ indicates the vector of active

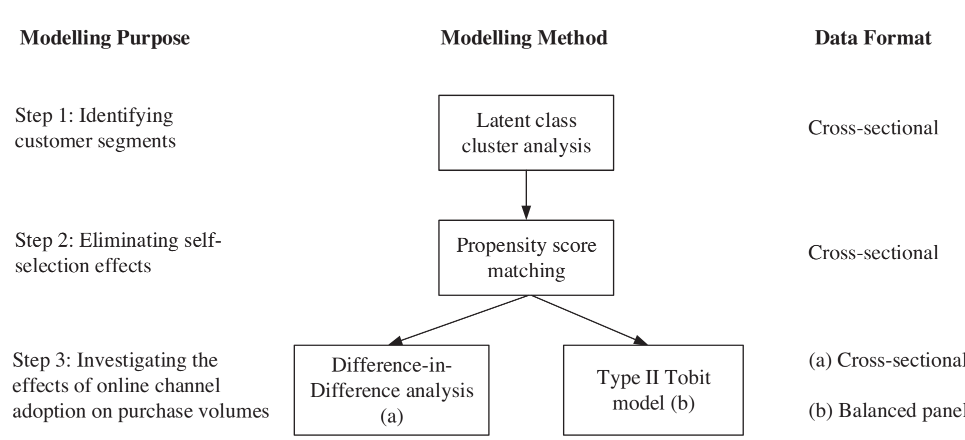

Fig. 3. Summary of Modeling Approaches.

Table 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; =0 otherwise
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.

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*[4] 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 $f(\boldsymbol{y}_i|z_i^{act\_cov})$ is the joint probability function of customer i's response to all indicators, as influenced by active covariates.

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 order size), relative to a control group of offline customers who do not adopt. We used PSM method to find a matched control group for each identified online adopter segment, which also controls for the self-selection bias. The basic idea of PSM method is to find matched samples (i.e., offline customers) who have the closest propensity scores to those of the treated group (i.e., online adopters). 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 method, we can ensure that the distribution of characteristics in the treated and matched groups is the same (Rosenbaum and Rubin 1985).

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.

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 behaviors 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).

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

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, Mela, and Neslin 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:

$$P_{it} = \text{Purchase}, \quad \text{if } P_{it}^* > 0; \quad \text{No Purchase}, \quad \text{if } P_{it}^* \leq 0 \tag{2}$$

$$P_{ii}^* = \beta_0 + \beta_1 Post_{it} + \beta_2 Post_{it} \times Treated_i + \beta_3 Gender_i + \boldsymbol{X_{it}\gamma} + \upsilon_{it} \tag{3}$$

$$Q_{it} = Q_{it}^*, \quad \text{if } P_{it}^* > 0; \quad \text{unobserved}, \quad \text{if } P_{it}^* \leq 0 \tag{4}$$

$$Q_{it}^* = \delta_0 + \delta_1 Post_{it} + \delta_2 Post_{it} \times Treated_i + \delta_3 Gender_i + \boldsymbol{X_{it}\theta} + \mu_{it} \tag{5}$$

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 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,[5] purchase from competitors, recency, and seasonality. To mitigate seasonal influences, we adopt Ansari, Mela, and Neslin (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. 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 3.

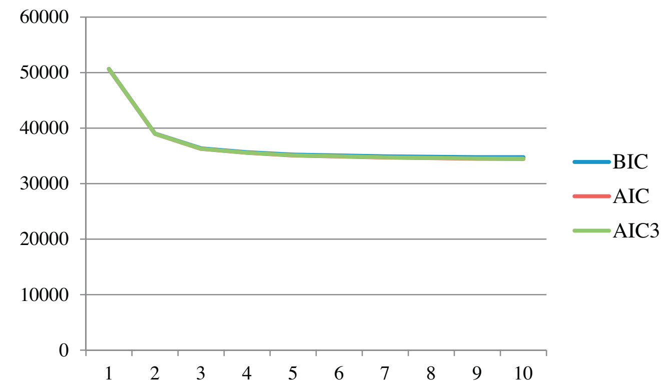

Fig. 4. Graphs of Model Selection Criterion.

Estimation Results

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 Konus, Verhoef, and Neslin (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 the derived segments. Among the statistical criteria, we primarily rely 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 Fig. 4. The values of the three criteria are close and keep decreasing with more segments, but Fig. 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.

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. Table 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 terminology 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.

[5] State-dependent variables are lagged variables that are defined differently in each equation. In Eq. (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 Eq. (4), which estimates order size, it is the order size of last purchase.

Table 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
Active Covariates												
Age	44	8	21	68	44	10	20	76	43	9	20	70
Gender (male)	4.97%				5.79%				2.74%			
Inactive Covariates												
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
Active Covariates								
Age	51	11	24	91	43	9	22	88
Gender (male)	1.76%				2.19%			
Inactive Covariates								
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 differs from our expectation: prior to the adoption of online channels, the late majority segment 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 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, Kumar, and Ravishanker 2007).

Parameter estimation. Table 5 contains the parameter estimations for the indicators and active covariates in the LCCA. Two indicators are statistically significant ($p < .001$) in most segments, suggesting that they effectively cluster the customer segments.

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 4.

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. In each segment, we chose the predictor variables that generated the best model fit, and in Table 6, we present the estimations of the parameters for five segments.

Table 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***	6144.474	0.000
Yearly purchase amount before adoption	10.8	−24.2***	−56.6***	146.0***	−75.9***	284.686	0.000
Active Covariates							
Age	−0.002	−0.010*	−0.017**	0.051***	−0.022***	44.2644	0.000
Gender (male = 1)	0.232	0.330*	−0.055	−0.343	−0.164	9.5435	0.049

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

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 innovators, 29 (9.32%) of early adopters, 84 (16.44%) of the early majority, 9 (5.29%) of the late majority, and 113 (24.73%) of laggards.

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 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 in relation to the selected characteristics with our PSM method.

Results of Difference-in-Difference Analysis

Table 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 essentially null 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 (marked by * in Table 8), 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, the 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.

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

Table 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.

Table 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

channels at different times, 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. We present the results of the purchase incidence model in Table 9 and the order size model in Table 10. 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 last transaction relates positively to current order size 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 affects 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, Shankar, and Ferraro 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. Economic recession relates negatively to purchase probability, but this effect is only significant for early adopters (−.155, $p < .01$). As for 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.

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 (i.e., innovator) or after (i.e., late majority and laggard) the online adoption date (results in Appendix A). Although 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 and order size 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.

Table 8
DID analysis.

	Online adopters			Offline customers		
	Before	After	Change	Before	After	Change
Innovator						
Total purchase amount (in Euros)	122.76	146.48	23.72*	122.48	135.54	13.07
	(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 (in Euros)	122.76	64.83	−57.93*			
	(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 (in Euros)	113.28	158.83	45.54*,#	140.70	153.54	12.85
	(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 (in Euros)	113.28	95.99	−17.29			
	(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 (in Euros)	94.82	183.54	88.72*,#	125.01	126.73	1.72
	(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 (in Euros)	94.82	106.64	11.82			
	(133.37)	(204.17)	(215.39)			
Offline purchase frequency	1.13	1.14	0.01			
	(1.55)	(2.31)	(2.33)			
Late majority						
Total purchase amount (in Euros)	383.55	347.01	−36.53	246.75	255.52	8.78
	(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 (in Euros)	383.55	268.55	−115.00*			
	(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 (in Euros)	71.22	133.26	62.04*,#	98.05	101.38	3.33
	(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 (in Euros)	71.22	69.68	−1.54			
	(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.

Thus, across various test periods, the early majority segment increases its monthly purchase amount after adopting the online channel.

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 B). Some minor differences arose, but the estimated results of the full data set are 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

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

that online channel adoption has no effect on customer purchase volumes in this segment (see Appendix C), which confirms our previous findings.

Discussion and Implications

We segmented customers on the basis of online adoption duration and purchase amounts before the adoption. We also investigated the effects of online channel adoption on customer purchases across multiple segments over time. For the discussion we address the two research questions that motivated our study.

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 them 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,

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

positive shopping experiences in a channel increase channel loyalty (Ansari, Mela, and Neslin 2008), especially if customers initiate their purchase process through offline channels (Dholakia, Zhao, and Dholakia 2005; Gensler, Dekimpe, and Skiera 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, Kumar, and Ravishanker 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 (Konus, Neslin, and Verhoef 2014; Valentini, Montaguti, and Neslin 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, Montaguti, and Neslin 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, Dekimpe, and Skiera 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? Earlier adopters remain valuable; however, 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, Kumar, and Ravishanker 2007; Xue, Hitt, and Chen 2011).

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.* The 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 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, Mela, and Neslin 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, Verplanken, and Knippenberg 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. In contrast, 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.[6] Heavy shoppers are more likely to give a high share-of-wallet to the company. 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 adoption. Liu (2007) supports this argument and proves 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.

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

[6] We thank an anonymous reviewer for suggesting this potential reason.

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 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 convenience or emphasizing its other benefits. Yet retailers cannot take the risk of ignoring their profitable contacts with these customers through existing offline channels.

Limitations and Further Research Directions

This research has several limitations that provide ideas for future research. First, we lacked information on the retailer's marketing activities in the three channels. Therefore, we detect the effects of marketing on customer purchases only indirectly. 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. Third, we did not distinguish different product categories or types, due to data limitations. As customer multichannel shopping behavior and the effects of online channel adoption differ across product types (Gensler, Leeflang, and Skiera 2012; Konus, Verhoef, and Neslin 2008), 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 customers' characteristics and their attitudes about multiple channels. 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.

Appendix A.

See Table A1.

Appendix B.

See Tables B1–B4.

Appendix C.

See Tables C1 and C2.

Table A1
Purchase incidence–order size model (48 months and 74 months).

Variable	48 Months				72 Months			
	Purchase incidence		Order size		Purchase incidence		Order size	
	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 .05.
** Significant at .01.
*** Significant at .001.

Table B1
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 B2
DID analysis (full sample).

	Online adopters			Offline customers		
	Before	After	Change	Before	After	Change
Innovator						
Total purchase amount (in	123.40	147.94	24.54*	117.51	141.14	23.63
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 (in	115.54	163.73	48.19*	141.83	162.92	21.09
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 (in	93.08	180.37	87.29*,#	129.80	127.72	−2.08
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 (in	483.38	432.77	−50.62	361.65	311.89	−49.76
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 (in	83.70	150.76	67.05*,#	118.75	129.92	11.17
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 B3
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 .05.
** Significant at .01.
*** Significant at .001.

Table B4
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 .05.
** Significant at .01.
*** Significant at .001.

Table C1
DID analysis: late majority segment.

	Online adopters			Offline customers		
	Before	After	Change	Before	After	Change
Late majority						
Total purchase amount (in Euros)	382.92 (315.58)	356.66 (316.00)	−26.26 (350.91)	253.07 (297.75)	261.91 (404.73)	8.83 (418.71)
Total transactions	4.36 (3.56)	4.32 (3.86)	−0.04 (3.93)	2.95 (3.33)	2.96 (3.81)	0.01 (3.65)
Offline purchase amount (in Euros)	382.92 (315.58)	273.81 (292.41)	−109.11* (336.03)			
Offline transactions	4.36 (3.56)	3.28 (3.47)	−1.09* (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 C2
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 .05.
** Significant at .01.
*** Significant at .001.

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