Remco Prins & Peter C. Verhoef

Marketing Communication Drivers of Adoption Timing of a New E-Service Among Existing Customers

This study investigates the effects of direct marketing communications and mass marketing communications on the adoption timing of a new e-service among existing customers. The mass marketing communications pertain to both specific new service advertising and brand advertising from both the focal supplier and the competitors. Using a split-hazard approach, the authors determine the effects of the considered marketing communications on adoption timing, accounting for a significant part of the customer base that never adopts the new e-service. They analyze individual adoption behavior with a sample of 6000 customers of a Dutch telecommunications operator over 25 months. The empirical results show that service advertising shortens the time to adoption, even when it is initiated by competitors. Furthermore, an exploratory analysis of the interaction effects between relationship characteristics and marketing efforts suggests that certain mass marketing efforts have a greater effect on loyal customers.

Successful new product/service introductions are important for a firm's long-term performance. This especially holds for industries in which firms invest heavily in technologies, such as mobile networks, under the premise that firms will be able to introduce new services using these technologies. For example, in Europe, telecommunications firms invested heavily in licenses for UMTS (Universal Mobile Telecommunication System) networks, paying €109 billion to the owners (i.e., the government) of these networks, in the hope that new 3G (third-generation) services would cause the saturated mobile telecommunications market to grow again (*The Economist* 2004). It soon became clear that the expectations about the UMTS technology were too high and that the actual rollout of 3G services would take several years longer. As a consequence, market values of telecommunications firms dropped considerably (Van Damme 2002). To get return on this type of technological investment, the new services based on the new technology should be successfully introduced. To achieve this, service providers must formulate an introduction strategy that focuses on both existing customers and potential new customers. Existing customers may be the most important target group for newly introduced products or services because they may be more likely to adopt the innovation as a result of their positive attitude toward the firm.

There is a large research stream in the marketing literature on new product adoption or trial by consumers (Meuter et al. 2005; Rogers 1995; Steenkamp and Gielens 2003). An important characteristic of this research stream is that it usually studies the adoption of new products or services in the total market, which consists of both existing customers and noncustomers. So far, researchers have not studied the adoption of new products or services among existing customers only. Moreover, many companies now consider their existing customers assets, which is reflected in the increasing importance of customer management in many industries (e.g., Boulding et al. 2005). From a customer management perspective, the cross-selling of new services to current customers can be a good strategy to increase the value of the customer base. If current customers adopt the new service, their customer lifetime value (CLV) should increase (Bolton, Lemon, and Verhoef 2004; Gupta, Lehmann, and Stuart 2004; Hitt and Frei 2002; Hogan et al. 2002; Rust, Zeithaml, and Lemon 2000), as long as the new service does not fully replace an existing one. Both the adoption itself and the timing of adoption are relevant in terms of a higher CLV because increased cash flows from a new product adoption occur earlier in the relationship, and prices of new services are often higher in the early stages of the product life cycle. In this study, we investigate marketing communication drivers of the adoption timing of a new e-service among existing customers.[1] We aim to contribute to both the adoption and customer management literature.

It is important to consider the difference between cross-buying or add-on buying of services and adoption of a new service among existing customers because it could be

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[1]Given our empirical focus on new service adoption, we mainly use the term "service" when discussing adoption. However, the theoretical discussion holds for both services and products.

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argued that new service adoption and cross-buying of additional services are the same insofar as both pertain to relationship expansion through buying more services (e.g., Verhoef, Franses, and Hoekstra 2001). However, there are some fundamental differences. First, cross-buying pertains to services that are already mature and known to the customer, whereas new service adoption involves products or services that are new to the world. This newness makes it a different buying decision because there is much more uncertainty about the characteristics and the usefulness of the new service. Second, cross-buying may also imply switching a service (e.g., a car insurance) from a competitor to the focal firm, whereas new product adoption implies buying a newly introduced service that is not yet purchased from competitors. Third, whereas cross-selling of services mainly focuses on existing customers through, for example, direct mailing and telemarketing (e.g., Verhoef, Franses, and Hoekstra 2001), the introduction of new services concerns the introduction both to the existing customers and to the total market. This causes large differences in the marketing communications that are used. Whereas cross-selling strategies mainly use below-the-line advertising, new product introductions may use both mass marketing communications and below-the-line advertising.

We contribute to the adoption literature as follows: First, this is the first study that considers the adoption timing decision solely among existing customers. Second, we broaden the scope of studied marketing communication drivers. In general, adoption studies consider the impacts of innovation characteristics, such as relative advantage, ease of use, risk, and complexity, and consumer characteristics, such as demographics and innovativeness (e.g., Arts, Frambach, and Bijmolt 2005; Manning, Bearden, and Madden 1995; Steenkamp and Burgess 2002). Recently, Steenkamp and Gielens (2003) have included (time-varying) marketing and communication efforts, such as advertising and promotions, as predictors of new product adoption in a consumer packaged goods context. However, attention to the impact of marketing communication efforts on new product or service adoption remains limited. In general, studies have ignored (1) the impact of individual-oriented marketing communication efforts (or direct marketing communications), such as direct mailings and e-mails; (2) the differential impact of marketing communication efforts that are specifically focused on the new product/service and those at the brand/company level;[2] and (3) the impact of competitive marketing communication at both the new product/service and the brand/firm level.

We contribute to the customer management literature as follows: First, new product adoption as a driver of customer equity has been almost completely ignored. For example, Bolton, Lemon, and Verhoef (2004) focus only on customer retention, service usage, and cross-buying as components of CLV in their CUSAMS (customer asset management of services) framework. Hogan and colleagues (2002) merely conceptually acknowledge the importance of new product adoption for customer profitability and CLV. Empirically, Hogan, Lemon, and Libai (2003) relate service adoption behavior to CLV and state that defecting new product adopters have a significant, negative impact on customer equity because of negative word of mouth. Recently, Kamakura, Kossar, and Wedel (2004) have developed a methodology to identify new product adopters for cross-selling purposes, using data on prior behavior as predictors, but they do not theoretically focus on drivers of new service adoption. Second, studies of the predictors of customer behavior mainly consider individual-oriented or customer-specific marketing interventions, or below-the-line advertising (Venkatesan and Kumar 2004). In this study, we include not only customer-specific marketing interventions but also above-the-line advertising expenditures over time, which do not vary across customers. As Bolton, Lemon, and Verhoef (2004) note, in general, advertising is associated with mass marketing, but Ambler and colleagues (2002) argue that brand advertising may increase the value of existing customers as well. Empirical evidence for this effect from advertising data remains scarce. Third, most studies in the customer management area do not include competitive instruments, though understanding customer responses to competitive actions is essential (Keiningham, Purkins-Munn, and Evans 2003). Therefore, we explicitly account for the effect of competitive advertising on individual customer adoption.

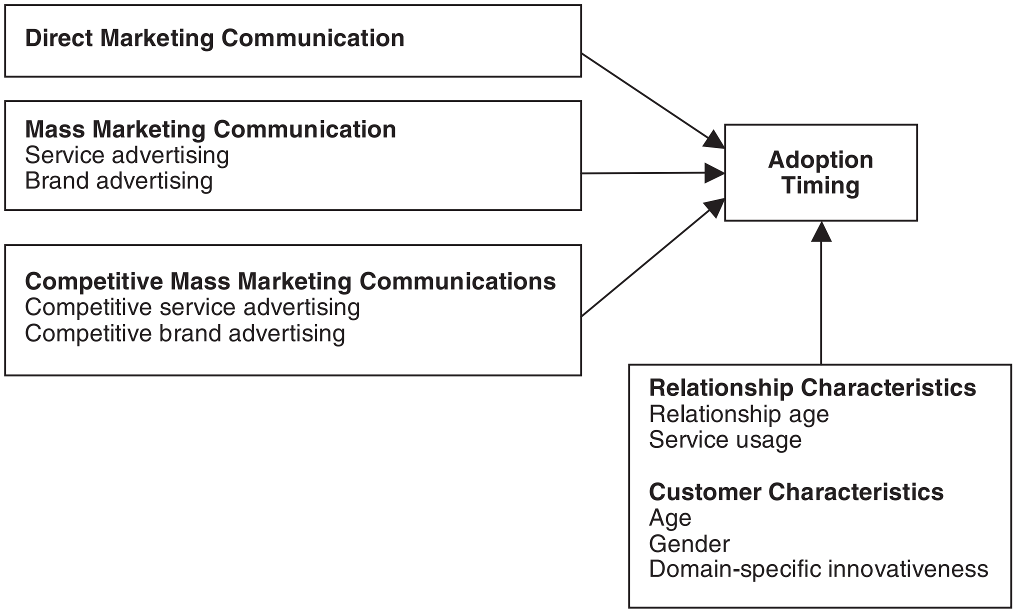
We organize the remainder of this article as follows: We begin with a discussion of our conceptual model, which we apply in the context of customer adoptions of a new e-service. Subsequently, we discuss our model to explain adoption timing. Note that we use a split-hazard model, which jointly models antecedents of the adoption probability and adoption timing. Then, we present the empirical results and key findings pertaining to the impact of various types of mass advertising on adoption timing and the different effects of customer-specific antecedents on adoption probability and timing. In addition, we report some significant interaction effects between mass marketing efforts and customer behavior. We conclude with a discussion of the findings, implications, and limitations of our study.

Conceptual Model and Hypotheses

We display our conceptual model in Figure 1. In this model, we study the effect of marketing communication efforts on the adoption timing of a new service. We define "adoption timing" as the time between the introduction and the adoption of the new service (Steenkamp and Gielens 2003). In this context, we define "adoption" as the actual buying of the new service by an existing customer. In our empirical model, we view adoption timing as conditional on adoption. We discuss this issue in greater detail in our "Methodology" section. In our model, the main focus is on the effect of marketing communication efforts because many studies in the new product diffusion literature have already shown that marketing efforts can have a significant effect on adoption rates at the aggregate level (Bass, Krishnan, and Jain 1994; Horsky and Simon 1983; Kalish 1985; Simon and Sebastian

[2]Note that this distinction is especially important for multiproduct or service firms, which advertise their brand (and a portfolio of offered products or services) and their newly introduced service to both potential and current customers.

FIGURE 1
Conceptual Framework



1987). We consider three groups of marketing communication variables that potentially explain adoption timing: (1) direct marketing communication efforts to existing customers pertaining to the new service, (2) mass marketing communication efforts (i.e., advertising) at the new service level and at the brand/firm level, and (3) competitive mass marketing communications at the new service level and at the brand/firm level. We also include a set of covariates to control for customer specific effects—namely, relationship characteristics (i.e., relationship age, service usage) and customer characteristics (i.e., age, gender, innovativeness).

Direct Marketing Communication

Direct marketing communications focus mainly on directly influencing existing-customer buying behavior (e.g., by providing attractive offers) and are essentially transaction oriented (Rust and Verhoef 2005). The effect of direct marketing communication on customer buying behavior has only recently gained attention in the academic marketing literature. Verhoef (2003) shows that direct marketing communication increases customer share. Venkatesan and Kumar (2004) report initial positive effects for reasonable amounts of direct marketing communications on purchase frequency, which become negative for large amounts of direct marketing communications (inverted U-shaped effect). Verhoef, Franses, and Hoekstra (2001) report positive effects of direct marketing communication on cross-buying. In the adoption literature, attention to direct marketing communication is lacking because of its focus on adoption behavior in the total market. Steenkamp and Gielens (2003) study other below-the-line actions, such as promotions, and show that these positively affect individual trial probabilities for consumer packaged goods. Together, these studies suggest that direct marketing communication focuses existing customers' attention on the new service, which may have a direct impact on their adoption behavior with respect to this new service. Thus:

> H_1: Direct marketing communication efforts shorten customers' time to adoption.

Mass Marketing Communication

Within the innovation diffusion/adoption literature, advertising is considered an important marketing tactic to diffuse the innovation in the market (e.g., Bass, Krishnan, and Jain 1994; Kalish 1985). On the individual consumer level, Steenkamp and Gielens (2003) show that mass advertising accelerates adoption among individual consumers. In general, advertising may create awareness and knowledge of the new service among both existing customers and other consumers. Next to awareness, advertising may also aim to inform potential adopters about the advantages of the new service, which may induce adoption. This will all be predominantly accomplished through advertising that specifically mentions the new service (i.e., new service advertising). Given the strong empirical results in the innovation/adoption literature, new service advertising most likely shortens adoption timing. However, as we noted previously, this literature studies all consumers and does not distinguish between existing customers and noncustomers.

Customer management researchers investigating antecedents of customer behavior usually do not include mass advertising efforts as a potential antecedent. A notable exception is Rust, Zeithaml, and Lemon's (2000) customer equity framework, which acknowledges the effect of branding on customer equity. However, in their modeling framework, they include both existing customers and noncustomers. The absence of the effect of mass advertising is explained by two reasons. First, from a data perspective, mass advertising data are not collected in customer databases, because they are available only at an aggregate weekly or monthly level. As a consequence, time-series data on customer behavior are required (i.e., per month) to match these aggregated advertising data. These data should be integrated with data from customer databases. Second, from a theoretical perspective, researchers have assumed that the behavior of existing customers is predominantly affected by company behavior within the customer relationship. Advertising plays a role mainly in attracting new customers (e.g., Bolton, Lemon, and Verhoef 2004). This might be true for behavior such as customer retention and cross-buying, but for newly introduced services, awareness should also be created among existing customers, and information on this new product should also be communicated to existing customers. This might be done through direct marketing communications. In addition, existing customers are likely to be confronted with mass advertising that promotes the new service, which should at least have some effect on customer behavior, in line with diffusion research. On the basis of this discussion, we hypothesize the following:

> H_2: Service advertising shortens customers' time to adoption.

Firms not only advertise newly introduced services but also continue their brand-focused advertising efforts. This brand advertising mainly aims to increase brand awareness; to improve brand attitudes; and to affect purchasing behavior, such as brand choice (e.g., Lodish et al. 1995; Rossiter and Percy 1997; Vakratas and Ambler 1999). The question is whether this brand advertising also positively affects the adoption of newly introduced services. An argument in favor of an effect is that brand advertising creates a more positive attitude toward the brand, which may positively affect the attitude toward the newly introduced service, which in turn may positively affect adoption behavior. In the same vain, Verhoef, Franses, and Hoekstra (2002) show that customers who are committed to the firm are more likely to buy additional services. However, we expect that the size of this effect is significantly smaller than the effect of specific service advertising, which directly aims to improve awareness for the new service and attitudes toward the brand. Thus:

> H_3: Brand advertising shortens customers' time to adoption.
>
> H_4: Service advertising shortens customers' time to adoption more than brand advertising.

Competitive Mass Marketing Communication

New services are usually not introduced by a single firm in the market. Competitors may introduce a similar service as well. These competitors also advertise their new service to stimulate adoption. Within the diffusion literature, particular attention has been given to the effect of this competitive advertising. It might be assumed that competitive service advertising negatively affects the adoption of the new service among existing customers of the focal supplier, but within the diffusion literature, there is ample evidence that competitive new service advertising may work positively. Indeed, it may even accelerate individual adoption through the market-making effect; that is, the advertising efforts of all competitors increase the penetration rate of new services (Krishnamurthy 2000; Krishnan, Bass, and Kumar 2000). Because of this higher penetration rate, competitors benefit from one another's advertising efforts pertaining to the new service, particularly in new markets with relatively few competitors (Mahajan, Sharma, and Buzzel 1993). Thus:

> H_5: Competitive service advertising shortens customers' time to adoption.

As does the focal supplier, competitors may also continue their brand advertising. Similar to the focal suppliers' brand advertising, competitive brand advertising aims to create awareness of the competing brand, to enhance positive attitudes toward the competing brand, and to affect buying behavior with respect to the competing brand. A possible consequence of competitive brand advertising is the enhancement of positive attitudes toward the competing brand among existing customers of the focal firm; it may also decrease brand attitudes toward the focal suppliers. In turn, this might negatively affect adoption. However, so far, evidence for these described effect paths is almost absent in the marketing literature. In their customer equity model, Rust, Zeithaml, and Lemon (2000) assume that when a firm increases its advertising, it creates higher perceived brand equity through increased brand awareness and positive attitude creation, which should lead to higher choice shares for the focal supplier and to lower choice shares for competing suppliers. Whether such an effect might also occur for new service adoption is an empirical question. However, for now, we formulate a hypothesis that is in line with our reasoning:

> H_6: Competitive brand advertising lengthens customers' time to adoption.

Interaction Effects Between Marketing Communication Efforts

In addition to the direct effects of these explanatory variables, we explore the interaction effect between direct marketing communication and mass marketing communication. Previous research (e.g., Naik and Raman 2003; Schultz, Tannenbaum, and Lauterborn 1993) points to a synergy between different marketing communication types (i.e., direct marketing communication and mass marketing communication), which should be reflected in a positive interaction effect. This positive interaction effect may occur, for example, because mass marketing communication, which creates awareness and positive attitudes for the new service, increases the effect of direct marketing communication. We have no reason to expect that there will be differences in these effects between service and brand advertising.

> H_7: There is a positive interaction effect between direct marketing communication and service advertising.
>
> H_8: There is a positive interaction effect between direct marketing communication and brand advertising.

Covariates

On the basis of prior research in the adoption and customer management literature, we include two groups of covariates in our model: relationship characteristics and customer characteristics. We view the relationship's length and depth as relationship characteristics (Bolton, Lemon, and Verhoef 2004). Several researchers have pointed out that relationship length may affect customer behavior (Dwyer, Schurr, and Oh 1987; Hitt and Frei 2002). However, this relationship may be nonlinear (Bolton, Lemon, and Verhoef 2004; Hitt and Frei 2002). In general, relationship depth, often referred to as "usage intensity" or "category usage," is considered an antecedent of trial or adoption probability (e.g., Steenkamp and Gielens 2003). Consumers who display high category usage levels have a greater category need and, therefore, a higher trial probability for a new product within that category (Gatignon and Robertson 1991). Again, there may be some nonlinearities in this relationship due to customer life-cycle effects (Bolton, Lemon, and Verhoef 2004).

The included relationship characteristics are of interest not only because of possible direct effects on adoption timing but also because there might be some interaction effects between relationship characteristics and communication efforts. Empirical research by Rust and Verhoef (2005) indicates significant heterogeneity of responses to marketing interventions that may be related to relationship characteristics. In particular, we explore the interactions between relationship age and direct marketing communication, (competitive) service advertising, and (competitive) brand advertising. Although the investigation of these interactions is not the primary objective of this study, we believe that it might provide valuable insights into the effects of marketing communication efforts on adoption, which could be studied in-depth in further research.

The customer characteristics we include as covariates are age, gender, and domain-specific innovativeness. These customer characteristics are likely to be important in the adoption probability and timing of individual customers (Arts, Frambach, and Bijmolt 2005). For example, in general, early adopters tend to be younger (Meuter et al. 2005; Rogers 1995). Customer innovativeness is also often considered an important antecedent of new product adoption. Most studies (e.g., Im, Bayus, and Mason 2003; Midgley and Dowling 1993; Steenkamp, Ter Hofstede, and Wedel 1999) focus on innate innovativeness as an individual trait that can be generalized over product categories and find that innovative people have a higher tendency to adopt new products and to adopt them faster. Citrin and colleagues (2000) and Goldsmith, Freiden, and Eastman (1995) show that domain-specific innovativeness, which reflects the consumer's tendency to try the latest innovations in a product category, has a stronger relationship to individual adoption behavior than does innate innovativeness. Our data provide information on the adoption of a previously introduced new service, which may be an indicator of domain-specific innovativeness. Thus, we control for domain-specific innovativeness in our model.

Data Description

Our empirical study focuses on the adoption process of a new mobile e-service in the Dutch consumer market, which a leading Dutch mobile telephone provider introduced in 2002. The new service uses GPRS (General Packet Radio Service) technology to give subscribers access to a range of Web sites specifically designed for mobile telephone use. For our empirical analyses, we employ the service provider's customer database, from which we gather monthly data on mobile subscribers, starting with the introduction date of the new service. These data include information on demographics, usage levels of various services, relationship characteristics, and marketing communication efforts by the provider. After the introduction of the new e-service, every customer could subscribe to it, in addition to their regular subscription with the mobile telephone operator. For each adopting customer, we know the first usage date of the new service, which enables us to determine the individual adoption times for customers who adopted the new service during the observation period.

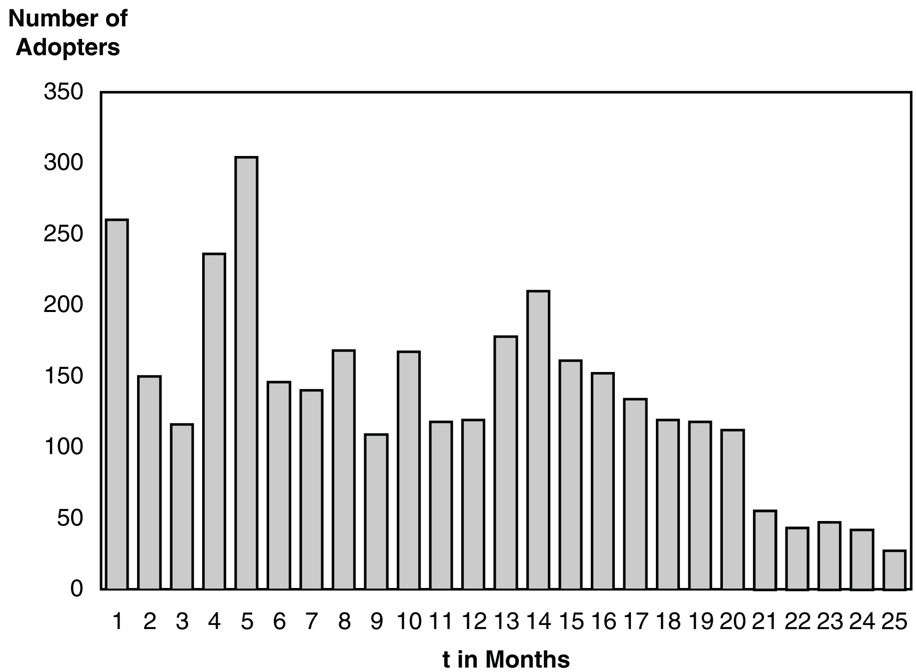
We chose to study adoption timing in this specific industry, for this specific company, and for this specific service for the following reasons: First, the telecommunications industry is known to collect data continuously on customer behavior in large databases, which enables us to study actual adoption behavior instead of reported or intended adoption behavior for existing customers. Second, the telecommunications industry has been a subject of research in prior adoption/diffusion and customer management research studies (i.e., Bolton 1998; Bolton and Lemon 1999; Simon and Sebastian 1987). Third, this industry is important in today's economies and is continuously introducing new services. Fourth, the introduction of this type of service is managerially relevant because these firms introduce the new services to get returns on their investments in technological networks. Fifth, this company was the first in the Netherlands to introduce this service; thus, the introduced service is fully new to the market. Finally, more from a practical standpoint in conducting successful collaborative research, there is a requirement to work closely with firms, which was possible with this firm because of positive previous experiences.

Sample

For our analyses, we randomly selected 6000 mobile subscribers from the provider's customer database who were current customers at the start of the observation period, which ran from August 2002 ($t = 1$) to August 2004 ($t = 25$). The start of the observation period is marked by the introduction date of the new service. By the end of the observation period, the number of existing customers adopting the new service rapidly declined (see Figure 2). Thus, we expect that the chosen observation period will capture the effects on adoption timing for most existing customers. Although all customers were with the provider at the start of the observation period, 910 left the provider before the end of the period. To avoid a selection bias, we did not exclude these customers from our sample.[3]

[3]Switchers to the competitive entrant's new service could have caused some of the defections, so these customers would be labeled as nonadopters even though they actually adopted the competitor's new service. Although no data were available on this issue, we believe that it is justified to label these customers as nonadopters because we specifically investigate the adoption of the focal company's new service among existing customers.

FIGURE 2
Monthly Adoptions in Sample



We were confronted with the issue of a relatively small adoption rate, which is not uncommon for multigenerational products or services because the users of the older technology will not immediately adopt the new one (Mahajan and Muller 1996; Pae and Lehmann 2003). It may take a significant amount of time before the diffusion of a new product really takes off (Golder and Tellis 1997; Tellis, Stremersch, and Yin 2003). Because we were particularly interested in the adoption of the new service but only a small portion of customers had adopted the service before September 2004, we oversampled these adopting customers. In our procedure, we oversampled the number of adopters so that approximately half the sample adopted the new service during the observation period, which gave us 3431 adopting customers, or 53% of the sample. Donkers, Franses, and Verhoef (2003) demonstrate that oversampling a rare event in binary choice models does not affect the parameter estimates or their standard errors, as long as the oversampling is not accompanied by stratified sampling on the independent variables. So far, no statistical research has shown that oversampling has an effect on the parameter estimates and standard errors of the split-hazard model. Thus, it is not clear what the effect of oversampling is on the split-hazard model results. Therefore, we estimated models with a smaller fraction of adopters. These models showed similar results in terms of sign and significance of the coefficients. However, models with few adopters have convergence problems, so we also estimated normal hazard models with different fractions of adopters. These results show that the sign of the coefficients do not change. For rather small fractions, however, a smaller number of variables becomes significant because of sample size effects. These additional analyses provided us with sufficient confidence in our estimation results.

Measures

Time to adoption. For each month in our observation period, we observed whether a customer adopted the new service. The time to adoption for each customer represents the time elapsed in months since the introduction of the e-service. We use the individual time to adoption as our observed dependent variable.

Marketing communication variables. During the observation period, the provider selected customers who would receive an individual offer by telephone to adopt the new service. Our data indicate whether and when each customer received an offer call from the provider. We operationalize these data by including a dummy variable that indicates the months in which the customer received the offer. Some customers who did not respond to the first offer were subsequently selected for a second offer. Although we recognize that the provider may have selected only those customers who were most likely to adopt in the first place, which would cause an endogeneity problem, we believe that by incorporating all possible selection criteria into our model, we can avoid serious problems in estimating the effect of direct marketing communication (Franses 2005; Shugan 2004).

We use data pertaining to monthly advertising expenditures to account for advertising effects on adoption timing. We retrieved these advertising data from BBC, a Dutch division of Nielsen Media Research International. Furthermore, we distinguish among service advertising, brand advertising, competitive service advertising, and competitive brand advertising for television, radio, print, outdoor, and cinema. We define "service advertising" as the provider's monthly expenditures (in millions of euros) on advertising that explicitly features the new e-service. In all cases, these advertisements mention the brand name of the provider as well, but the main focus is on the new service. We define "brand advertising" as the provider's expenditures on advertising that is not directly related to the new e-service.

Although the e-service was new to the market at the time of introduction by the provider, six months later, one of its competitors launched a similar service. Therefore, we include "competitive service advertising," or the competitor's advertising that explicitly features a similar e-service. Again, the competitor mentioned its brand name in all these advertisements. Finally, we include "competitive brand advertising," which is all competitors' advertising that is unrelated to any similar e-services. To allow for possible lagged advertising effects, we also include all advertising expenditures in the previous month.

Covariates. As noted, we include relationship age and service usage as covariates. We define relationship age as the number of years the customer had been with the provider at t = 1, the start of the observation period. To measure the service usage, we compute the average monthly amount spent by each customer over his or her total customer lifetime before the start of the observation period. Thus, service usage does not include usage of the newly introduced e-service.

The customer demographics we control for are gender and age. We set the gender dummy to zero for male customers, and we define the age variable as the customer's age in years at the start of the observation period, so that it is fixed over time. As a proxy for the domain-specific innovativeness of each customer with respect to mobile e-services, we include a dummy variable that indicates the adoption and use of a prior generation mobile e-service, which was introduced several years before. Table 1 summarizes and describes all our included variables.

TABLE 1
Measurements and Descriptives of Explanatory Variables

Variable	Label	Average	SD
Marketing Communication			
Direct Marketing Communication			
Dummy for individual offer by telephone for customer i in month t	DMC_{it}	.09	.13
Mass Marketing Communication			
Service Advertising			
Advertising expenditures in millions of euros in month t related to the new service	SA_t	1.11	.88
Brand Advertising			
Advertising expenditures in millions of euros in month t not related to the new service	BA_t	1.50	1.05
Competitive Mass Marketing Communications			
Competitive Service Advertising			
Advertising expenditures of all competitors in millions of euros in month t related to a similar service	CSA_t	.95	1.12
Competitive Brand Advertising			
Advertising expenditures of all competitors in millions of euros in month t not related to a similar service	CBA_t	6.23	2.44
Relationship Characteristics			
Relationship Age			
Number of years customer i has been with the provider at t = 1	RA_i	2.67	1.65
Service Usage			
Average monthly amount spent by customer i before t = 1	SU_i	3.39	4.03
Customer Characteristics			
Gender			
(male = 0, female = 1)	$Gend_i$	.26	.43
Age			
At t = 1	Age_i	37.93	10.45
Domain-Specific Innovativeness			
Dummy for usage of prior generation e-service by customer i	$Innov_i$	.03	.18

Methodology

Adoption studies that consider adoption a discrete event use a logit or probit-like model to assess the impact of independent variables on adoption (e.g., Meuter et al. 2005), whereas those that investigate adoption timing tend to use a hazard model (e.g., Steenkamp and Gielens 2003). The hazard model makes the assumption that, eventually, every consumer will adopt the new product. Especially for products and services with greater technological complexity, a significant group of consumers will never adopt. Theoretically, this issue has been pointed to as innovation resistance and is reflected in rejecting the new service, opposing the new service, or postponing the adoption of the new service (e.g., Bagozzi and Lee 1999; Mittelstaedt et al. 1976; Ram and Sheth 1989; Szmigin and Foxall 1998). For example, this innovation resistance may be caused by consumers being comfortable with the current situation, not perceiving the advantage of the new service, or considering it a risky innovation. Sheth (1981) concludes that consumers who resist innovations tend to be different from consumers who do not resist innovations.

The notion that a group of customers will probably never adopt the new service has important implications in the study of the antecedents of adoption timing. Not only are these consumers unaffected by the time elapsed after the introduction of the product, but we also assume that they are "immune" to any marketing efforts. In other words, the probability of adoption for these consumers is zero. A traditional hazard approach does not account for this group, because it assumes that all consumers are "at risk" for adoption after the product's introduction. In practice, we cannot observe whether a consumer belongs to the immune group, but we can estimate the probability of eventual adoption by each consumer using available customer characteristics.

The econometric model accounting for the problem—that a significant portion of the consumers will never adopt—emerges through the split-hazard approach. Developed by Schmidt and Witte (1989), this split-hazard approach has been applied in various contexts, including new product adoption (e.g., Chandrashekaran and Sinha 1995; Dekimpe et al. 1998; Kamakura, Kossar, and Wedel 2004; Sinha and Chandrashekaran 1992). Following this methodology, we apply a split-hazard approach to model both the adoption probability and the adoption timing of the new service by existing customers. Thus, the time to adoption for individual i, denoted as T_i, is a random variable with a cumulative distribution function F(t) and density $f(t) = F'(t)$. The probability that adoption has not yet occurred at time t is provided by the survivor function $S(t) = 1 - F(t)$. The hazard rate $h(t) = f(t)/S(t)$ can be defined as the conditional likelihood that adoption will occur at time t, given that adoption has not occurred yet. We can observe adoption only for the consumers who adopted within the period of observation (0, T); those who did not adopt before time T will either be censored and adopt at some time beyond T or never adopt at all. The split-hazard model enables us to estimate simultaneously the probability of eventual adoption and the time to adoption. We include a dummy variable that indicates adoption by the end of the month in the hazard part of our model as the failure indicator. Customers are considered at risk of adoption as long as they have not adopted the new service. Those customers who left the provider during the observation period can be included in the analysis only for the periods in which they remained with the company.

We model adoption timing as a hazard function of both time-varying marketing communication efforts and the time-invariant covariates (i.e., relationship characteristics and customer characteristics). The baseline hazard function follows a prescribed distribution and captures the longitudinal regularities in adoption time dynamics, separate from the effects of the covariates. In other words, it captures the effect of the time elapsed since the introduction of the new product. The parametric form we use for our hazard function is the complementary log-log model, which is particularly useful when data from discrete time intervals are used for a continuous underlying adoption process because the estimates of the model do not depend on the length of the time intervals (Allison 1982; Van den Bulte and Lilien 2001). To account for (nonlinear) time dependencies of the baseline hazard rate, we include a time-trend variable and the squared time trend in the hazard part of our model. Higher-order transformations result in significant coefficients but capture too much of the effects of the time-varying variables, such as advertising effects. Therefore, we allow only for a first- and second-power time dependency of the baseline hazard in our model.

We represent the hazard part of our model, including all explanatory variables, as follows:

$$
\begin{aligned}
(1)\quad h_{it} = 1 - \exp[-\exp(&\beta_0 + \beta_1 \times t + \beta_2 \times t^2 + \beta_3 \times DMC_{it} \\
&+ \beta_4 \times SA_t + \beta_5 \times SA_{t-1} + \beta_6 \times BA_t + \beta_7 \times BA_{t-1} \\
&+ \beta_8 \times CSA_t + \beta_9 \times CSA_{t-1} + \beta_{10} \times CBA_t \\
&+ \beta_{11} \times CBA_{t-1} + \beta_{12} \times RA_i + \beta_{13} \times RA_i^2 + \beta_{14} \times SU_i \\
&+ \beta_{15} \times SU_i^2 + \beta_{16} \times Age_i + \beta_{17} \times Age_i^2 + \beta_{18} \times Gend_i \\
&+ \beta_{19} \times Innov_i)].
\end{aligned}
$$

Simultaneously, we estimate the unobserved probability of eventual adoption for every individual customer, which we denote as p_i. We model the probability of eventual adoption as a logit function of time-invariant customer characteristics and relationship characteristics:

$$
\begin{aligned}
(2)\quad p_i = 1/[1 + \exp(&\gamma_0 + \gamma_1 \times RA_i + \gamma_2 \times RA_i^2 + \gamma_3 \times SU_i \\
&+ \gamma_4 \times SU_i^2 + \gamma_5 \times Age_i + \gamma_6 \times Age_i^2 + \gamma_7 \times Gend_i \\
&+ \gamma_8 \times Innov_i)].
\end{aligned}
$$

The log-likelihood function of our total model (including Equations 1 and 2) is as follows:

$$
\begin{aligned}
(3)\quad LL = \sum_{i=1}^{N} &d_i \times \ln\left[p_i \times h_{it} \times S_{it-1}\right] \\
&+ (1 - d_i) \times \ln\left[(1 - p_i) + p_i \times S_{it}\right],
\end{aligned}
$$

where

h_{it} = hazard rate from Equation 1,
p_i = probability of eventual adoption from Equation 2,
d_i = censoring indicator (1 if observed, and 0 if censored), and
S_{it} = survival rate.

For observed adoptions, the censoring indicator d_i equals 1. The contribution to the likelihood function by consumer i at time t is the probability that he or she will eventually adopt, as given by p_i, multiplied both by the conditional probability of adoption at t, as given by the hazard rate h_{it}, and by the probability that he or she has not adopted before t, as given by the survival rate S_{it-1}. Censored observations, for which d_i is 0, belong to either the nonadopters, with probability $(1 - p_i)$, or those who will eventually adopt but have not yet, given by the terms $p_i \times S_{it}$. To obtain the coefficients for every explanatory variable, we use maximum likelihood estimation in STATA Version 8.2.

Results

To assess whether the split-hazard model is required, because we assume that a significant part of the existing customers will probably never adopt the new e-service, we also estimated an ordinary proportional hazard model. Note that these models are nested. When we compare the fit of our split-hazard model with the proportional hazard model, it shows that our model has a significantly better fit, according to the likelihood-ratio test: $\chi^2(9) = 27.546$, $p < .01$. Furthermore, the Akaike information criterion (AIC) statistic of the split-hazard model is smaller (27,229.89 versus 27,239.44), which indicates a better fit. The Bayesian information criterion (BIC) statistic does not show an improvement, which would imply that the split-hazard model does not do a better job in explaining adoption timing than the ordinary hazard model. Note that the BIC penalizes more complex models more heavily than the AIC. However, on the basis of our theoretical justification of the split-hazard approach in the "Methodology" section and of the other diagnostics, we believe that the split-hazard model is theoretically the best way to model individual adoption timing (see also Kamakura, Kossar, and Wedel 2004). Moreover, according to the STATA program, it is rather difficult for the more complex split-hazard model to deliver a better fit. Still, two of our three fit measures favor the split-hazard model. Thus, we discuss only the results of the split-hazard model. The ordinary hazard model does not lead to different conclusions with respect to the variables of interest.[4]

Table 2 summarizes the results of the split-hazard model. In the logit part of our model, positive coefficients indicate a positive effect on the probability of eventual adoption, whereas in the hazard part, positive coefficients indicate a positive effect on the hazard rate. Consequently, variables with positive coefficients shorten the time to adoption. The estimation results reveal some significant effects of our included relationship characteristics in the logit part of the model, indicating that the nonadopters (or customers who resist the innovation) are indeed different from the adopters. The results also reveal significant effects of the considered marketing communications. We now discuss our results more specifically.

Marketing Communications

Direct marketing communications have a significant, positive effect on the hazard rate; these effects substantially shorten consumers' time to adoption. We also find a positive effect for service and brand advertising on adoption timing. When we test for the equality of the coefficients of service and brand advertising, we find that the effect of service advertising is significantly greater than that of brand advertising ($p < .01$). Therefore, H_1, H_2, H_3, and H_4 are all supported. In addition, our hypothesis about the market-making effect of competitive service advertising (H_5) is confirmed; we find a positive, significant effect on adoption timing. Finally, competitor brand advertising has a significant, negative effect, which implies that it lengthens the time to adoption, as H_6 predicts. Overall, the lagged effects of advertising expenditures are not significant, except for that of brand advertising.[5] The size of all mass advertising effects is considerably smaller than the size of the direct marketing communication effects (i.e., no increase in advertising expenditures can equal the effect of a direct marketing communication offer on individual hazard rates). However, the stronger direct marketing communication effect may be context dependent, as we discuss in our "Discussion and Implications" section.

Covariates

Relationship age has a significant (nonlinear) effect on adoption probability. Specifically, the probability of eventual adoption increases as the age of the customer's relationship with the provider increases, up to approximately three years. For customers who have been with the provider for more than three years, the adoption probability decreases. To some extent, this finding is in line with that of Reinartz and Kumar (2003), who report a nonlinear relationship between interpurchase times and lifetime duration. We do not find a significant effect of relationship age on adoption timing.

Service usage appears to be a significant indicator of both adoption probability and adoption timing. Customers with high usage levels are less likely to adopt the new service eventually than are customers with low usage levels. This effect might occur because customers with high usage levels are satisfied with the services they currently receive and thus have no need to adopt a new service. Given that

[4]These estimation results are available from the first author on request.

[5]We also performed an additional analysis to assess further the potential long-term effects of the included marketing communications; specifically, using Nerlove and Arrow's (1962) approach, we considered the cumulative effects of advertising expenditures for all four types of marketing communications. Our estimation results did not reveal any cumulative effects for the focal supplier's service and brand advertising or for competitors' service advertising. We found an unexpected positive effect of cumulative competitive brand advertising. Given the absence of strong support for cumulative advertising effects, we do not report these effects.

TABLE 2
Estimation Results

	Logit Part: P(Adoption)		Hazard Part: Time to Adoption	
	Coefficient	z Value	Coefficient	z Value
t	N.A.		.1618	11.49***
t^2	N.A.		–.0048	–9.82***
Direct marketing communication	N.A.		1.8652	43.20***
Service advertising	N.A.		.2243	7.22***
Service advertising (t – 1)	N.A.		.0012	.05
Brand advertising	N.A.		.0521	2.25**
Brand advertising (t – 1)	N.A.		.0432	1.88*
Competitive service advertising	N.A.		.0969	4.85***
Competitive service advertising (t – 1)	N.A.		–.0065	–.29
Competitive brand advertising	N.A.		–.0863	–10.26***
Competitive brand advertising (t – 1)	N.A.		–.0078	–.85
Relationship age	.8493	1.75*	.0521	1.00
Relationship age^2	–.1296	–1.86*	–.0033	–.42
Service usage	–.2164	–3.00***	.0580	4.45***
Service usage^2	.0032	2.35**	–.0009	–2.45**
Age	–1.6270	–.88	–.2123	–1.55
Age^2	.2413	.97	–.0075	–.46
Gender	.4401	.62	–.1486	–2.44**
Domain-specific innovativeness	–.2685	–.44	.3166	2.84***
Constant	5.5730	1.67*	–3.6189	–11.98***
Log-likelihood	–13,586.947			
Likelihood ratio test	$\chi^2(28)$ = 1935.99***			
AIC statistic	27,229.89			
BIC statistic	27,401.83			

*p < .10 (two-sided).
**p < .05 (two-sided).
***p < .01 (two-sided).
Notes: N.A. = not applicable.

they adopt, customers with high usage levels turn out to be the fastest adopters. This positive relationship between service usage and adoption timing suggests that despite a low adoption probability, heavy users tend to adopt faster than light users.

Interaction Effects

In addition to our analyses of the main effects displayed in Table 2, we perform an analysis on any possible interaction effects between direct marketing communication and mass marketing communication and between marketing communications and relationship characteristics. We include all interaction terms simultaneously in the split-hazard model we used previously, which does not change the other coefficients significantly. Therefore, we report only the interaction effects and relevant main effects in Table 3. Adding the interaction effects to the model improves the total model fit significantly ($\chi^2(7) = 24.724$, $p < .001$); the AIC statistic also decreases from 27,229.89 to 27,219.17.

The first interaction effect we investigate is that between direct marketing communication and service and brand advertising. The results suggest a negative interaction effect between direct marketing communication and service advertising, which indicates that the combined effect of the two types of marketing efforts on adoption timing is less than the sum of the separate positive effects. The interaction effect between direct marketing communication and brand advertising is not significant. Therefore, we do not find evidence for communication synergies between direct marketing communication and brand advertising, as H_7 and H_8 predict.

The second interaction effect we examine is that between relationship age and all types of marketing communications. The results suggest that the influence of service advertising efforts, whether by the provider or its competitors, is greater for customers who have been with the provider for a longer time. We did not find any significant interaction effects between (competitive) brand advertising and relationship age or between direct marketing communication and relationship age.

Discussion and Implications

In this study, we investigate the effects of marketing communications on the individual adoption timing of a new e-service by existing customers of a large Dutch telecommunications provider. In doing so, we integrate the literature streams of new product adoption and customer management. This integration and our data—including customer adoption behavior, customer-specific marketing

TABLE 3
Estimation Results Interaction Effects

	Hazard Part: Time to Adoption	
	Coefficient	**z Value**
Direct marketing communication (DMC)	1.9558	16.44**
Service advertising (SA)	.1841	4.88**
Brand advertising (BA)	.0323	1.06
Competitive service advertising (CSA)	.0829	3.48**
Competitive brand advertising (CBA)	–.0819	–8.01**
Relationship age (RA)	–.0345	–.41
RA^2	.0038	.36
DMC × SA	–.1226	–1.97*
DMC × BA	.0424	.92
RA × DM	–.0202	–.43
RA × SA	.0742	2.89**
RA × BA	.0004	.02
RA × CSA	.0380	2.12*
RA × CBA	–.0059	–.71
Log-likelihood	–13,574.585	
Likelihood ratio test	$\chi^2(35)$ = 1960.71**	
AIC statistic	27,219.17	
BIC statistic	27,434.09	

**p* < .05 (two-sided).
***p* < .01 (two-sided).

interventions, advertising expenditure data, customer relationship characteristics, and customer characteristics—enable us to contribute to both literature streams. Table 4 reports a summary of our hypothesis-testing results; we discuss our most important findings and contributions next.

First, we study both direct marketing communication and mass marketing communication. These mass marketing communications include both advertising that communicates the new e-service and brand advertising, and we also consider the impact of these two advertising types from competing suppliers. In support of prior customer management research findings, we find that direct marketing communication shortens adoption timing (Verhoef, Franses, and Hoekstra 2001). This is an important extension of the knowledge pertaining to the possible effects of direct marketing communication. For example, it influences not only cross-buying of existing services but also the purchase of newly introduced services. The finding of an effect of direct marketing communication is also important for the adoption literature because so far, adoption researchers have ignored the impact of this type of communication on individual adoption behavior. Our study results emphasize the importance of direct marketing communication in influencing existing-customer adoption behavior. Consistent with previous adoption studies and diffusion research, we find a positive effect of the focal supplier's mass advertising expenditures on individual customers' adoption speeds. However, the effect on adoption timing is remarkably smaller than the effect of direct marketing communication. This could be because in this particular setting, mass communications, due to their focus on creating awareness and information provision, do not influence adoption behavior strongly. To affect behavior, more action-oriented communications, such as direct marketing communication, are required. However, this stronger effect of direct marketing communication may also be because we study the adoption behavior of existing customers, who might be more responsive to individually targeted marketing efforts. Furthermore, this result may be context dependent because we could investigate only one type of direct marketing communication and we did not have any influence on the content of the message. For example, it might have been possible for the provider to adjust the message to the individual customer's situation. Moreover, the strong effect of direct marketing communication might also be due to the firm doing a good job of selecting customers to contact by telephone. However, we controlled for this by including several covariates. Overall, we cannot draw any generalizable conclusions from the relatively strong direct marketing communication effect compared with the effect of mass marketing communications. Further research might aim to replicate our findings.

Second, this is the first study to distinguish explicitly between brand advertising and service advertising. We show that the effects of each type of mass advertising on individual adoption timing are notably different. Mass advertising that is specifically related to the new service has a greater effect on the time to adoption than does general mass advertising for the service provider's brand. This is not an unexpected finding, because service advertising has a more specific focus on the new service. Through service advertising, service providers mainly build consumer

TABLE 4
Summary of Hypothesis Testing Results

Variable	Hypothesis	Hypothesized Effect on Adoption Timing[a]	Finding	Conclusion
Direct marketing communication (DMC)	H_1	+	+	Supported
Service advertising	H_2, H_4	+	+	Supported
Brand advertising	H_3, H_4	+	+	Supported
Competitive service advertising	H_5	+	+	Supported
Competitive brand advertising	H_6	–	–	Supported
DMC × service advertising	H_7	+	–	Not supported
DMC × brand advertising	H_8	+	n.s.	Not supported

[a]Positive effects indicate a shorter time to adoption.
Notes: n.s. = not significant.

awareness and interest with respect to the new service category. However, the positive effect of general brand advertising on adoption behavior is remarkable. On the basis of general advertising theories, we argue that brand advertising positively affects attitude toward the brand, which in turn positively affects adoption behavior. However, there is still much that is unknown about this effect. For example, do improved brand perceptions positively affect adoption behavior? In this study, we did not account for intervening brand attitudes (or service attitudes). It would be worthwhile to include these attitudes in more extended models in further research. As we noted, customer management research has ignored mass advertising for several reasons. Our study shows that mass communications indeed affect adoption behavior of existing customers. This is an important finding, though it might be due to the specific nature of the behavior; namely, existing customers also need to be informed about the new service, which suggests a more important role of mass advertising. However, it may also point to a too narrow view of customer management researchers, who assume that after acquisition, existing customers focus mainly on the relationship itself and are no longer affected by mass advertising efforts. In general, the important role of advertising is acknowledged in frequently consumed packaged goods, for which advertising elasticities are found to be between 0 and .2 (Assmus, Farley, and Lehmann 1984; Vakratas and Ambler 1999). In these markets, advertising is required to reinforce the brand position continuously in the consumers' minds to affect buying behavior and, thus, brand loyalty in the store. The question is whether advertising also affects existing customers' behaviors, such as customer retention or cross-buying, in long-term (contractual) relationships. Our study may indeed point to the existence of these effects. However, further research should empirically establish whether these effects are actually present.

Third, our results show that competitive advertising efforts that feature similar services can accelerate the adoption process for first movers as well, which suggests that through service advertising, service providers mainly build consumer awareness and interest with respect to the new service category. It also confirms the market-making effect, which has been shown to be relevant at the aggregate diffusion level (e.g., Krishnan, Bass, and Kumar 2000). Our study is the first to show this effect at the individual adoption level. Our results also show that competitive brand advertising lengthens adoption timing. This finding is notable because it shows that even the adoption of new services by existing customers is affected by competitive actions that are not related to the specific new service. Theoretically, we reasoned that this effect might exist because of the effects of competitive advertising on brand attitudes of both the focal supplier and the competitor. However, we have no empirical evidence for this link, because we do not observe brand attitudes. More research is required here. The inclusion of competitive mass communication efforts is new for the customer management research literature. Most researchers have ignored the impact of competitive actions, though such actions are acknowledged to be relevant (e.g., Keiningham, Purkins-Munn, and Evans 2003). Our results emphasize the importance of these competitive actions. A next step in customer management research would be for researchers to include more competitive variables in their models.

Fourth, we examined various possible interaction effects in our analysis. Although we expected a positive synergy between direct marketing and mass marketing efforts, we find some rather less straightforward effects, including an unexpected negative interaction between service advertising and direct marketing communication. Prior research has also identified some negative interaction effects. Naik, Raman, and Winer (2005) argue that the price-oriented nature of promotions may reduce the effectiveness of advertising in building brands. Conversely, advertising may lower consumer sensitivity to promotions. Narayanan, Desiraju, and Chintagunta (2004) report a negative interaction effect between detailing and advertising in pharmaceutical markets. Bass and colleagues' (2005) reasoning is that there might be a kind of overkill. The advertising combined with direct marketing communication may result in too much attention for the new service, resulting in a negative interaction effect. Overall, additional research is required to understand these negative interaction effects, which are found more commonly in empirical research. We cannot find any significant interactions between brand advertising and direct marketing communication, which implies that there is no synergy between these marketing variables.

The interaction effects between marketing efforts and relationship age provide more intuitive results. Service advertising has a greater impact on more loyal customers, and the positive interaction effect between competitive service advertising and relationship age implies that the market-making effect does not work well for relatively new customers. Overall, the interaction effects between relationship age and marketing efforts provide further evidence that customers' heterogeneous responses to marketing efforts may be explained, at least partially, by relationship characteristics, such as relationship age (Rust and Verhoef 2005).

Fifth, from a modeling perspective, our research shows that it is important to account for the notion that certain customers will probably never adopt the new service. This supports the theoretical notion of innovation resistance mentioned in the adoption literature. So far, most adoption researchers do not account for this in their econometric model (e.g., Steenkamp and Gielens 2003). Thus, our study is one of the few studies to use a split-hazard model that accounts for this effect at the individual adoption level. However, we should mention that our model might also work well because of the limited time frame of the data. Usually, the takeoff of a new product or service may take several years (Tellis, Stremersch, and Yin 2003). Thus, we do not observe adoption for a large part of the existing customers included in our study; our model might consider such customers nonadopters, but they might adopt the product several years from now. However, recent adoption figures pertaining to the studied new service still show a limited number of adopters (see also Figure 2), indicating that innovation resistance might indeed be a problem. Notably, the split-hazard model may also have other applications in customer management research. For example, when modeling relationship duration, it might be assumed that there is a group of customers who are unlikely to churn (e.g., because of high switching costs) and that there is another group of customers who are at risk for churning. The latter group might be receptive to service improvement efforts, whereas the former group is almost nonresponsive. So far, researchers have not acknowledged modeling relationship duration that accounts for the appearance of these two groups of customers (e.g., Bolton 1998).

Sixth, our study is the first to investigate customer adoption of new services using data from a customer database. These data offer some notable insights, especially with respect to the effects of behavioral relationship characteristics on customer adoption behavior. Customers who have been with the provider for two or three years have the highest probability to adopt the new e-service eventually. The lower adoption probability for new customers may be explained by the contractual setting; these customers are still locked in to their recently established contract with the provider, and upgrading to a contract that includes the new service would be costly. The low adoption probability of customers who have been with the provider for a long time could be explained by customer life-cycle effects, such that in the later stages of the customer life cycle, customers are not likely to adopt new products or services. Customers with high usage levels, who are assumed to have a deeper relationship with the provider, are less likely to adopt the new service, which seems counterintuitive. However, customers with high usage levels who adopt indicate a relatively short time to adoption. Furthermore, we find that domain-specific innovativeness does not affect the probability of eventual adoption, but it shortens the time to adoption. A note of caution is required here because our measure for domain-specific innovativeness might be imperfect. Further research might, for example, use perceptual innovativeness measures instead of our behavioral indicator.

Management Implications

Speeding up the adoption of newly introduced services is important to many firms. This especially holds in the telecommunications industry, in which services are linked to large network technology investments. A successful introduction of these new services is required to get return on these investments. Existing customers are an important target group in the introduction of new services. However, the question is which marketing communications the firm should use to speed up adoption. Our results indicate that firms can use both direct marketing communication and mass marketing communication to shorten adoption timing. However, the effect of direct marketing communication is much larger than the effect of mass marketing communication. Thus, our results seem to suggest that speeding up adoption timing among existing customers should mainly be done with direct marketing communication. The role of mass marketing communication is only limited. However, mass marketing communication may still be required to reach noncustomers as well. Conversely, a strategy might be to focus on existing customers first to create a sufficiently large customer base to spread the new technology into the market further. This might point to potential cost savings for firms if they first use relatively cheap and more effective direct marketing communications and then use the existing customer base to create network effects.

Our results also show the importance of competitive advertising effects on the new service. Thus, a useful strategy might involve two or more competitors that simultaneously introduce a new service; this approach should accelerate the adoption process for every player in the market.

The results of our study, particularly the exploratory analyses of the interaction effects between marketing efforts and relationship age, reveal a significant role of customer loyalty in existing customers' adoption process. We find that loyal customers adopt sooner than relatively new customers and have a better response to mass marketing efforts. Therefore, building customer loyalty is important not only for customer retention and cross-selling but also for the adoption of new and additional services.

Research Limitations and Further Research

Our study has several limitations that suggest possible directions for further research. First, we consider only one service introduction in the telecommunications industry for a specific company. The question is whether our findings are generalizable to other contexts as well. This specific industry, company, and service have specific characteristics (e.g., a high degree of technological turbulence, high involvement, one of the larger market players). For example, in markets with lower-involvement products, the effects of mass advertising are likely to be smaller. Further research is required to study the effect of marketing communications on adoption behavior. Studying other industries and services would make it possible to study which market and service characteristics moderate the effects of marketing communications.

Second, we focus on the adoption behavior of existing customers only. Accordingly, our findings apply to this group alone. However, a considerable number of adopters were not customers of the provider before they adopted the new service. These customer acquisitions as a result of the introduction of the new service were not observed by the provider before the adoption, so we did not account for them. It would be worthwhile to investigate the specific effects of marketing communications on the adoption behavior of this specific group of consumers.

Third, we do not have any data about prices, income levels, or customer attitudes. Prices will most likely have a considerable impact on customers' adoption timing, but such data typically are difficult to retrieve in a mobile service context. Including customer attitudes in the model, such as customer satisfaction and the perceived usefulness of the new service, would also be a possible extension that could provide new and valuable insights into individual adoption behavior (e.g., Meuter et al. 2005).

Fourth, our results are limited to the communication types and content this provider used. For example, the direct marketing communication efforts consisted of telephone calls from the provider to existing customers. The found effects might be different if other instruments or content were used. Therefore, we cannot generalize our findings on the relative size of the effects of direct marketing communication and mass marketing communication on adoption timing. Further research might consider how instruments and content moderate the effect of marketing communications on adoption behavior.

Finally, we defined individual adoption as a dichotomous event—that is, the first trial of a new service. Continuous usage of the new service may be a better characterization of the adoption decision because some adopters could cease to use the service after the first trial. Therefore, a promising direction for further research would be to investigate postadoption usage and disadoption of new services in a customer management context.

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