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CONTENTS

TABLES

FIGURES

Chapter 1

Introduction

1.1 MODELING BEHAVIOR IN CUSTOMER RELATIONSHIPS

Customer relationship management (CRM) is common practice in many firms today. These firms see their customers as assets and realize they need to be managed accordingly (Kumar, Lemon, and Parasuraman 2006). The core of a CRM strategy is to develop strong relationships with customers (Boulding et al. 2005; Reinartz, Krafft, and Hoyer 2004). With regard to its current customers, a firm can focus on customer expansion or customer retention. Customer expansion can be realized by means of up-selling and cross-selling, both of which involve the adoption of another product or service* by the customer. In the case of up-selling, the adoption is a more profitable version of the current product; and in the case of cross-selling, the adoption of an additional product is implied (Prins and Verhoef 2007). Thus, managers need to understand and be able to predict customer adoption behavior to create value by means of an expansion strategy. A retention strategy implies that a firm aims to develop long-lasting relationships with its profitable customers. To identify the customers at risk of leaving, such that managers can reach them in time, they need models that produce accurate estimates of customer churn probabilities. In summary, modeling behavior in customer relationships such as adoption and churn is crucial for firms in developing a successful CRM strategy.

* We use the words product and service interchangeably in this chapter. We acknowledge the differences between the two, but these are not relevant in this context.

A recent development which has substantial consequences for customer behavior is the increasing importance of social networks in consumers' daily lives. In the increasingly networked society, consumers are connected to each other via multiple platforms, such as email, mobile telephony, online social networks, blogs, and review sites (Libai et al. 2010). Compared to traditional face to face communications, these platforms enhance social interactions on a large scale with little effort. Another notable difference with face to face communication is that these new platforms are all digital in nature, which allows researchers to observe interactions and collect social network data.

This development has two major consequences for modeling behavior in customer relationships. First, the availability of social network data allows researchers to incorporate the behavior of related others in the traditional models. Thus, researchers can explain and predict individual behavior in customer relationships using both individual customer data and data on other customers in the network. With these extended models one can quantify the effect of social influence on customer behavior, which is the effect of a related other's behavior. Second, the availability of network data provides the opportunity to analyze new behaviors, such as the behavior of a network (that is, the behavior of consumers who are all related to the same individual). Researchers can investigate how their behavior is affected by the behavior and characteristics of the related customer, and thus determine what makes a customer more influential than others. Figure 1.1 provides an overview of the key publications in each cell of the two (individual or network data) by two (individual or network behavior) framework.

		BEHAVIOR	
		Individual customer	Network of the customer
DATA	Individual customer	– Bijmolt et al. 2010 – Bult and Wansbeek 1995 – Lemmens and Croux 2006 – Malthouse and Derenthal 2008 – Neslin et al. 2006	– Hinz et al. 2011 – Katona, Zubcsek and Sarvary 2011 – Schmitt, Skiera and van den Bulte 2011
	Network of the customer	– Hill, Provost and Volinsky 2006 – Iyengar, van den Bulte and Valente 2011 – Manchanda, Xie and Youn 2009 – Nitzan and Libai 2011	– Goldenberg et al. 2010

Figure 1.1: Key publications on modeling behavior in customer relationships

In this thesis we focus on modeling behavior in customer relationships from a network perspective. In the remaining part of this first chapter we will introduce the topics that are covered in the thesis. In section 1.2 we provide a short discussion on the traditional CRM approach and the scoring models that are commonly used to predict behavior in customer relationships. In section 1.3 we introduce the customer engagement concept and illustrate its relevance for CRM. We discuss the role of customer-to-customer (c2c) interactions and social networks in CRM in section 1.4. We continue with a discussion about social influence on behavior in customer relationships in section 1.5. In section 1.6 we formulate our key research questions and in section 1.7 we describe the setting of this research. We present the main contributions in section 1.8. Finally, we provide an outline of the thesis in section 1.9.

1.2 SCORING MODELS

1.2.1 Scoring models in customer relationship management

There is a large stream of research discussing statistical models to explain and predict behavior in customer relationships, such as adoption, cross-sell, up-sell, and retention (e.g., Neslin et al. 2006; Verhoef 2003). Bijmolt et al. (2010) present an overview of the models that are typically used for these purposes. In line with the extant literature, we refer to those as scoring models (Malthouse and Derenthal 2008; Verhoef et al. 2010). In this thesis we focus on the two most commonly used scoring models in the marketing field, namely logistic regression and decision trees (Neslin et al. 2006).

1.2.2 Staying power of scoring models

Many studies describe one scoring model in detail or compare different types of models in order to find the one that has the greatest predictive power in a particular setting at a particular moment. The predictive power is often assessed with a hold-out sample or a one-period-ahead forecast. The performance over a longer time span, the so-called staying power, is typically ignored (Neslin et al. 2006). Marketers use the predictions of behavior in customer relationships, such as churn, to target campaigns and calculate metrics like customer lifetime value (CLV). This illustrates the importance of accurate predictions, which becomes even more apparent if managers use CLV metrics for marketing resource allocation purposes (Venkatesan and Kumar 2004). Regular re-estimation of the models is costly, but accuracy of the predictions is crucial, thus rendering the concept of staying power quite important.

1.3 CUSTOMER ENGAGEMENT

Studies on individual level scoring models have produced numerous insights which have enriched our understanding of behavior in customer relationships (Verhoef, Van Doorn, and Dorotic 2007). However, in the current networked society this transaction-oriented approach is becoming too limited since customers can easily share their experiences and opinions with other customers and firms around the globe. These nontransactional behaviors are likely to affect the behavior of others and thus affect the value of the customer to the firm (Kumar et al. 2010; Van Doorn et al. 2010). The recently introduced concept of customer engagement behavior broadens the scope of customer management by including nontransactional behavior. It is defined as "a customer's behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" (Van Doorn et al. 2010). Customer engagement acknowledges the effect of c2c interactions on the value of the customer to the firm (Libai et al. 2010; Verhoef, Reinartz, and Krafft 2010). To incorporate customer engagement in models for behavior in customer relationships, information from customers' social networks can be used. They provide information on how customers are related to each other and thus help to identify the effects of social influence, e.g., word of mouth.

1.4 SOCIAL NETWORKS

1.4.1 Social networks in marketing

The analysis of customer network data is a relatively new topic in the area of customer relationship management (Libai et al. 2010; Van Doorn et al. 2010). The recent burst in the availability of customer-to-customer interaction data has triggered the interest of marketers who have been looking for ways to use the knowledge on these interactions for marketing purposes. This is illustrated by the huge social network ad revenues that are expected to rise to 7.72 billion USD in 2012 (eMarketer 2012) and by the exceptionally high valuations of social network sites (Baldwin 2011; Graig and Sorkin 2011). Despite the large number of papers that provide evidence for the existence of the positive effects of c2c interactions on customer behavior, understanding of the phenomenon is still limited (Iyengar, Van den Bulte, and Choi 2011).

1.4.2 Customer-to-customer interactions

Libai et al. (2010) provide the following formal definition of customer-to-customer interactions: “the transfer of information from one customer (or a group of customers) to another customer (or group of customers) in a way that has the potential to change their preferences, actual purchase behavior, or the way they further interact with others (p. 269).” C2C interactions occur in various ways and settings, but they can be classified using five dimensions: observational learning vs. verbal communications, online vs. offline venues, dyadic vs. group information flows, B2C vs. B2B markets, and organic (occurring naturally) vs. amplified (firm-initiated) interactions (Libai et al. 2010). The interactions that we focus on in this thesis are offline, dyadic, organic and verbal in a B2C setting. By linking c2c interactions and individual behavior in customer relationships, we can infer to what extent a customer’s behavior is affected by the behavior of others and we can investigate what drives the influence that an individual exerts on those in his/her network.

1.4.3 Network data

C2C interactions can be described by means of a network where the customers are the actors and the interaction is a tie between them. This representation allows researchers to use social network analysis techniques that have been developed mainly in sociology (Van den Bulte and Wuyts 2007; Van den Bulte 2010). In this thesis we focus on networks consisting of an individual (ego) and all the individuals to which s/he is directly connected (alters). Although we do not include the ties between the alters, we refer to those networks as ego networks. To study social influence on behavior in customer relationships, the definition of the network is crucial. Thus far, most studies have used either self-reported data or geographical data (zip codes) to build a network. Although the use of surveys is common (Wasserman and Faust 1994), they have several drawbacks, including dependence on respondents’ memories, differences across respondents’ interpretations, and self-report biases (Bertrand and Mullainathan 2001), all of which can lead to erroneous descriptions of the network. Geographical data are also commonly used because most customer and marketing databases contain zip code information (Bell and Song 2007; Nam, Manchanda, and Chintagunta 2010). However, social interaction is not measured directly, and so the use of these data requires the assumption that people living close to each other influence each other (Choi, Hui, and Bell 2010; Iyengar, Van den Bulte, and Choi 2011). It is unlikely to be an accurate description since social interaction is becoming less and less dependent on spatial proximity (Goldenberg et al. 2010; Haenlein 2011; Iyengar, Van den Bulte, and Choi 2011).

As an alternative, online social networks are a potentially rich source of network data. The number of people in these networks is typically large, and data are relatively easy to obtain (Godes and Mayzlin 2004; Lewis et al. 2008; Stephen and Galak 2010; Trusov, Bucklin, and Pauwels 2009). A disadvantage of this method is the difficulty in combining network information and behavioral data for the same person. Furthermore, people are typically connected in an online network to many others who are not relevant from a social influence perspective since it requires only very little effort to establish and maintain a 'friendship' tie (Ackland 2009; Trusov, Bodapati, and Bucklin 2010).

In order to overcome these limitations, we used the call detail records (CDR) of a mobile telecom operator to create networks. In CDR data, all phone calls and text messages are recorded individually. A person's mobile phone network is a good proxy for his or her social network (Eagle, Pentland, and Lazer 2009; Haythornthwaite 2005) and has been used in prior research to model retention (Nitzan and Libai 2011) and adoption (Hill, Provost, and Volinsky 2006).

1.5 SOCIAL INFLUENCE

1.5.1 Social influence on customer behavior

Although social influence is currently one of the key research areas in marketing, it is not new to the field. We define social influence as the influence of related others on the probability that a person will show certain behavior. We infer this influence from associations between the behaviors of related individuals. The positive effects of social influence on behavior are well-established in the literature; they have been found across different behaviors, products, and industries using different methodologies (e.g., Bell and Song 2007; Nitzan and Libai 2011). However, it remains unclear why social influence occurs under certain circumstances and why some customers are more influential than others. Recently, several authors have proposed to shift our focus in these directions to gain a deeper understanding of the phenomenon (Godes 2011; Iyengar, Van den Bulte, and Choi 2011). There are two interesting phenomena to study: First, to what extent an individual customer is affected by the behavior of his/her social network. Despite the growing number of papers in this area, two factors that are commonly studied for other marketing instruments have been mostly overlooked, namely the dynamics of social influence effects and the interactions with other marketing instruments. We discuss those topics in the next two subsections. The second phenomenon is what determines the influence of an individual customer on the behavior of his/her network. Several determinants have been identified in different fields, but it remains unclear what the main determinant is and whether these determinants are product- and behavior-specific. We discuss these issues in subsection 1.5.4.

1.5.2 Dynamics of social influence and direct marketing

Many studies in marketing have shown that the effects of marketing instruments may vary over time (e.g., Leeflang et al. 2009; Osinga, Leeflang, and Wieringa 2010; Pauwels et al. 2004; Van Heerde, Srinivasan, and Dekimpe 2010). Surprisingly, the effects of social influence are typically assumed to be constant, but there are several reasons why these effects are likely to be time-varying. First, from the time of introduction onwards, the total number of adopters in the market will increase and therefore the normative influence on consumers is likely to increase. As a result, consumers will likely be less affected by the influence from those in their ego network. Second, the amount of information about a new product in the market increases over time, which will make the impact of additional information smaller. Thus, the information a consumer receives from related others is likely to have a smaller effect on his/her behavior. Third, consumers that adopt early are likely to differ from those who adopt later and thus the effect of social influence on adoption is likely to differ as well. Therefore, dynamic effects of social influence should be considered in models for behavior in customer relationships.

1.5.3 Social influence and traditional marketing instruments

As mentioned earlier, social influence and social networks are expected to play a major role in marketing strategies. Therefore it is crucial to understand how traditional marketing instruments and social influence interact (Libai et al. 2010). Positive inter-actions, or synergies, can occur because social influence may increase awareness for a new product among consumers, which may increase the likelihood of responding to a marketing action. These synergies have been found between other marketing instruments (Naik and Raman 2003; Naik, Raman, and Winer 2005; Narayanan, Desiraju, and Chintagunta 2004). However, negative interactions may also occur. Consumers may develop a positive attitude towards a product based on social influence, but this positive attitude may be tempered when the firm interferes with these private interactions, because consumers may feel reactance towards the product as a result of the firm's marketing action (Godfrey, Seiders, and Voss 2011).

1.5.4 Determinants of social influence

Research on the determinants of social influence has been executed in different areas. As a result, several perspectives on what determines social influence have evolved. We classify the determinants in three groups: network characteristics, customer relationship characteristics, and personal characteristics. These different approaches have given us many insights into the social influence phenomenon, but we have also identified a number of unresolved issues. The key issues that we investigate in this thesis are whether social influence is mainly determined by network characteristics, customer relationship characteristics, or personal characteristics; and whether the impact of the determinants differs across products and behaviors.

1.6 RESEARCH FRAMEWORK

The Chapters 2, 3, and 4, which form the core of the thesis, differ on the two dimensions that we touched upon in the first section of this chapter, namely 1) the scope of the data that is used to model behavior in customer relationships (individual customer vs. network of the customer) and 2) the level of the behavior under study (individual customer vs. network of the customer). Figure 1.2 shows the two-by-two framework and the position of the three chapters. With the three studies and this framework we address our main research objective:

To extend models for behavior in customer relationships with a social influence dimension.

We define four research questions in line with this objective:

1. *What is the staying power of commonly used scoring models?*
2. *How does the social influence effect depend on the time since product introduction?*
3. *How do social influence and direct marketing interact?*
4. *What are the key determinants of social influence on behavior in customer relationships?*

We answer the research questions in the three core chapters of this thesis. In Chapter 2 we employ the traditional approach of modeling individual behavior in customer relationships using individual customer characteristics. However, to address research question 1 we extend current research by investigating the staying power of commonly used methods. That is, we analyze the accuracy of the predicted probabilities over a longer time span. In Chapter 3 we address research questions 2 and 3. We build on the traditional models for individual behavior in customer relationships and add social network characteristics as explanatory variables in the model. That is, we take into account that consumers are not isolated decision makers, but that their behavior is possibly affected by the behavior of others in their social network. More specifically, we study the dynamics of social influence effects and the potential synergy between social influence and direct marketing. In Chapter 4, we again go one step further to address research question 4 and analyze to what extent the behavior of an individual customer affects the others in his/her network. We investigate the determinants of this influence and show why some consumers are more influential than others.

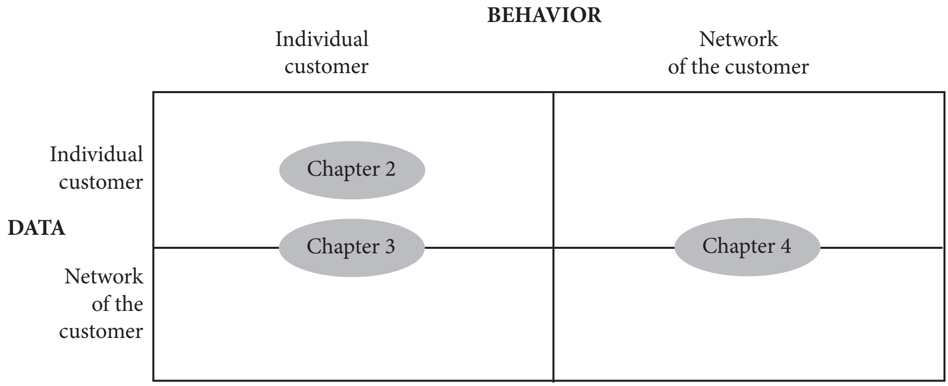

Figure 1.2: Framework of the core chapters of this thesis

1.7 MOBILE TELECOM INDUSTRY

For the research presented in this thesis, we have predominantly used data from the mobile telecom industry. This industry is very suitable for modeling behavior in customer relationships from a network perspective for several reasons. First, mobile phones and subscriptions are sold on a contractual basis which enables a telecom operator to collect customer characteristics and track behavior over time. Furthermore, the moment that a customer churns can be observed in a contractual setting (Fader, Hardie, and Ka 2005). Second, detailed information on phone calls and text messages allowed us to create the networks of the customers that we used in Chapters 3 and 4. Because a telecom operator has access to both the network data and the customer database, these data sources can easily be merged. Using individual customer IDs, we could add the results from an online survey[†]. Such a rich combination of data is hard to collect in any industry other than the telecom

† All data were made anonymous because of privacy concerns and legal restrictions before they were made available to the researchers.

industry. Third, telecom operators regularly introduce new products and services ranging from free mobile services to expensive and complex high-technology products. This allowed us to study behavior in customer relationships in different product and behavior settings as discussed in Chapter 4.

1.8 THEORETICAL CONTRIBUTION

The contribution of this thesis is that we provide novel insights on the two key concepts in customer relationship management, namely building and maintaining good relationships with customers, with a focus on the role of social influence among customers.

First, we contribute to the literature on scoring models that are commonly used to model behavior in customer relationships. Whereas most studies focus on finding the best model for one particular setting at one point in time (e.g., Lemmens and Croux 2006; Levin and Zahavi 2001), we use data over a longer period of time in multiple settings and show that the staying power of commonly used scoring models is low. This implies that building new models or at least re-estimating existing ones on a regular basis is of utmost importance to obtain accurate predictions.

Second, we contribute to the area of social influence research in marketing because we go beyond merely showing that social influence occurs by investigating several factors that affect social influence. We present five key findings: (1) social influence is decreasing from the product introduction onward, (2) social influence is equal to the direct marketing effect during the first four months after the product introduction and dominated by that effect afterwards, (3) there is no synergy between social influence and direct marketing, (4) social influence is mainly driven by network characteristics, and (5) the determinants of social influence are behavior- and product-specific.

1.9 OUTLINE OF THE THESIS

In the next chapter we investigate the staying power of several commonly used churn scoring models. In Chapter 3 of this thesis, we investigate the dynamics of the social influence effect and analyze whether social influence and traditional marketing strengthen each other or function as substitutes. In Chapter 4, we empirically investigate the determinants of social influence and compare the impact of the determinants of social influence across different products and behaviors. In Chapter 5, we summarize the main findings of the research described in Chapters 2, 3, and 4. Then we formulate an overarching conclusion, suggest managerial implications, and propose avenues for future research.

Chapter 2

Staying Power of Churn Prediction Models‡§

2.1 INTRODUCTION

Churn management, being a part of Customer Relationship Management (CRM), is of utmost importance for firms, since they strive for establishing long-term relationships and maximizing the value of their customer base (Bolton, Lemon, and Verhoef 2004; Rust and Siong 2006). Losing a customer negatively affects a company in a number of ways. First, it leads to an immediate decrease in sales revenue and given that a company will have to attract more new customers when churn rates are higher, it will lead to an increase in acquisition costs (e.g., Athanassopoulos 2000; Rust and Zahorik 1993). Moreover, in the cas e of services that are sold on a contractual basis, losing a customer is not just a product less sold, but in fact the well-defined termination of a relationship[1]. Potential future cash flows by means of cross- or upselling are lost (Gupta, Lehmann, and Stuart 2004). Hence, accurate predictions of churn probabilities are a key element of customer lifetime value calculations and CRM in general (Blattberg, Malthouse, and Neslin 2009; Donkers, Verhoef, and De Jong 2007; Dreze and Bonfrer 2008; Fader and Hardie 2007; Gupta 2009; Pfeifer and Farris 2004). The

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‡ This chapter appeared as Risselada, Hans, Peter C. Verhoef, and Tammo H.A. Bijmolt (2010), "Staying Power of Churn Prediction Models," *Journal of Interactive Marketing,* 24(10), 198-208.

§ We thank a Dutch telecommunications company for providing the data, and Aurélie Lemmens for providing the S-code for the bagging algorithm. We thank Jenny van Doorn for her helpful comments and Jaap Wieringa for sharing data. We thank the editor Ed Malthouse and two anonymous reviewers for their helpful comments.

importance of accuracy becomes even more apparent if CLV is used for marketing resource allocation (Venkatesan and Kumar 2004).

In the literature several churn model approaches have been discussed. The most commonly used methods are classification trees and logistic regression models (Neslin et al. 2006). Recently, machine learning based methodologies, such as bagging and boosting, have been applied (Ha, Cho, and MacLachlan 2005; Lemmens and Croux 2006). Bagging consists of averaging the results of multiple models that have each been estimated on a bootstrap sample from the original sample. Studies reporting the predictive performance of these models usually only consider hold-out sample or one-period-ahead validation. For example, Lemmens and Croux (2006) predict churn probabilities for one period after the estimation period. In these studies little attention is paid to the staying power. That is, how well a model predicts in a number of periods subsequent to the estimation period (Neslin et al. 2006).

Knowledge on the staying power provides database marketers with a framework to reconsider the methods used for churn modeling and to assess for how long an estimated model can be used. This in turn will help to improve CLV predictions, since they depend heavily on churn probabilities. Hence, insights on the staying power of churn prediction models can be used to determine a reliable time horizon of CLV calculations (Blattberg, Malthouse, and Neslin 2009). However, obtaining accurate predictions comes at a cost; gathering the right data, cleaning up the data sets, and estimating a model can be very time-consuming (e.g., Malthouse and Derenthal 2008). Hence, a balance between model accuracy and model building efficiency is desirable. To increase the model building efficiency we investigate in what way models need to be adapted over time. These insights can make the process of churn prediction less cumbersome, and thereby save time and money.

In this study we use two customer databases, one from a large internet service provider and one from a health insurance company, to analyze the staying power of the most commonly used churn models, namely the logit model, the classification tree, and both methods in combination with a bagging procedure. To evaluate the staying power the top-decile lift and Gini coefficient are calculated for different time periods.

The results show that the application of a bagging procedure has little effect on the predictive performance of the logit models, but that it increases the accuracy of the predictions of the classification trees. Overall, the classification tree in combination with a bagging procedure leads to the highest predictive performance over time. However, the staying power of all models is low, as the predictive performance deteriorates considerably after the estimation period. Furthermore, we find that for all models the significance and size of the parameter estimates vary over time. In sum, our results show that the optimal strategy for our data sets is to regularly estimate a new classification tree in combination with a bagging procedure and start the modeling process with selecting the appropriate variables for that particular period.

The contribution of this study to the existing literature on churn modeling is twofold. First, this is the first study in the customer management literature that investigates the staying power of churn prediction models over a longer time span. Previous research mainly used hold-out samples or one-period ahead validation. Since CLV calculations depend heavily on predicted churn probabilities this study also contributes to the literature on CLV calculation and CLV-based marketing resource allocation (e.g., Blattberg, Malthouse, and Neslin 2009; Venkatesan and Kumar 2004). Second, we more specifically contribute to the churn modeling literature by testing the predictive power of prediction methods in two industries, namely the internet service provider and insurance markets. In the extant literature, some researchers have shown a superiority of bagging in one industry (Lemmens and Croux 2006), while others suggested a better performance for the logistic regression in another industry (e.g., Donkers, Verhoef, and De Jong 2007). Hence it is important to test the predictive power of churn models across multiple industries (Verhoef et al. 2010).

The remainder of this chapter is structured as follows. In the next section we present a concise overview of the literature on scoring models. In section 2.3 we describe the data, followed by the methodology in section 2.4. In section 2.5 we describe the results for the two data sets separately and in the last two sections we summarize our main findings and formulate avenues for future research.

2.2 MODELING CHURN

2.2.1 Scoring models

In the literature various methods for churn analysis have been described. These methods are very similar to those traditionally used in the direct marketing field, since identification of customers that are likely to churn is similar to the identification of customers that are likely to respond to a mailing. Analogous to other papers in this area (e.g., Malthouse and Derenthal 2008; Verhoef et al. 2010) we will refer to these models as scoring models. Two scoring models that have extensively been studied in the marketing field are logistic regression models and classification trees (see Table 2.1). In the marketing literature several studies have compared the two, but did not reach a consensus on a clear winner; the observed differences in the performance of the two methods were often rather small (Hwang, Jung, and Suh 2004; Levin and Zahavi 2001; Neslin et al. 2006).

Although more sophisticated models have been studied within marketing, such as neural networks (Zahavi and Levin 1997), random forests (Buckinx and van den Poel 2005; Coussement and van den Poel 2008; Larivière and van den Poel 2005), multiple adaptive regression splines (Deichmann et al. 2002), ridge regression (Malthouse 1999), and support vector machines (Coussement and van den Poel 2008), they have not yet gained widespread popularity due to limited gains in accuracy and a substantial increase in complexity (see Table 2.1)[2]. This is supported by Neslin et al. (2006), who found that logistic regression models and classification trees accounted for 68% of the entries of a churn modeling contest in which both practitioners and academics participated.

In sum, prior marketing literature suggests that logistic regression models and classification trees are commonly used by academics and practitioners and that both methods have good predictive performance. However, based on the aforementioned papers a superior method has not been identified.

Scoring models have been applied in many research areas other than marketing, for example the machine learning field. In that field three large-scale comparative studies have appeared, in which the performance of many different models, including logistic regression models and classification trees, has been assessed on a large number of data sets (King, Feng, and Sutherland 1995; Lim, Loh, and Shih 2000; Perlich, Provost, and Simonoff 2004). A general conclusion is that the performance of a particular method depends heavily on the characteristics of the data. King, Feng, and Sutherland (1995) find that the logistic regression model is outperformed by the tree-based methods if the data is far from normal and contains many categorical variables. However, Perlich, Provost, and Simonoff (2004) emphasized that the size of the estimation sample has a major impact on the performance, and hence they argued that comparisons can not be made on a single version of a data set. In their study, logistic regression outperformed classification trees on smaller data sets ($n \approx 1{,}000$), but the opposite held for larger data sets. Furthermore, they found that performance is influenced by the signal-to-noise ratio; the higher this ratio, the better the classification trees perform. If signal and noise are hardly separable there is a high risk of over fitting with tree based methods due to the "massive search" of the algorithms (Perlich, Provost, and Simonoff 2004).

Table 2.1: Scoring model literature framework

Study	*Literature stream*	*Compared methods (of interest)*	*Number of periods*	*Main findings*
King, Feng, and Sutherland 1995	Machine Learning	– logistic regression – classification trees (among many others)	1	– No single best algorithm. – Performance depends on the characteristics of the data set. – Overall, discriminant and regression algorithms perform well in terms of accuracy. – These methods performed well on the data sets on which the tree algorithms performed worse. – Tree algorithms are accurate if the data has extreme distributions. – Logistic regression is a bad choice if the data is far from normal and if there are many categorical variables in the data. – Tree algorithms are the easiest to use and understand.
Lim, Loh, and Shih 2000	Machine Learning	– logistic regression – classification trees (among many others)	1	– Differences in error rates of many algorithms are statistically insignificant. – Classification trees perform well and are easiest to interpret.
Perlich, Provost, and Simonoff 2004	Machine Learning	– logistic regression – classification tree – both+bagging	1	– Logistic regression performs better for smaller data sets. – Tree induction performs better for larger data sets. – Higher signal-separability situation is favorable for trees. – Classification trees: bagging often improves accuracy, sometimes substantially. – Logit: bagging is detrimental.
Buckinx and van den Poel 2005	Marketing	– logistic regression – random forest – neural network	1	– Differences among techniques are statistically insignificant.
Coussement and van den Poel 2008	Marketing	– logistic regression – support vector machines (SVM) – random forest	1	– SVM outperforms the logistic regression, only when the appropriate parameter-selection technique is used. – Random forests approach outperforms SVM. – The trade-off between time allocated to the modeling procedure and the performance is emphasized.

Study	*Literature stream*	*Compared methods (of interest)*	*Number of periods*	*Main findings*
Deichmann et al. 2002	Marketing	– multiple adaptive regression splines combined with logistic regression (hybrid approach) – logistic regression	1	– MARS+logit is slightly better than logistic regression. – The use and interpretation of MARS is complicated. – MARS is not widely available.
Ha, Cho, and MacLachlan 2005	Marketing	– logistic regression – neural network – neural network+bagging	1	– Neural network+bagging outperforms both the neural network and logit.
Haughton and Oulabi 1993	Marketing	– CART – CHAID	1	– CHAID performs slightly better for problems with many categorical variables. – The best solution is to use both CART and CHAID, compare the results and choose the best.
Hwang, Jung, and Suh 2004	Marketing	– logistic regression – neural network – classification tree	1	– Methods perform similarly.
Kumar, Rao, and Soni 1995	Marketing	– logistic regression – neural network	1	– Neural networks account for complex relationships in the data and produces better classification than the logistic regression. – The logistic regression technique has a closed form solution and is easier to interpret.
Larivière and van den Poel 2005	Marketing	– logistic regression – random forest	1	– The random forest approach performs better than the logistic regression.
Lemmens and Croux 2006	Marketing	– classification tree – classification tree+bagging	1	– Tree+bagging outperforms the single classification tree.
Levin and Zahavi 2001	Marketing	– classification trees – logistic regression	1	– The logistic regression model outperforms the other models, but the differences are small. – Classification trees are easier to use and interpret.

Study	*Literature stream*	*Compared methods (of interest)*	*Number of periods*	*Main findings*
Neslin et al. 2006	Marketing	– logistic regression – classification tree – classification tree+bagging (see Lemmens and Croux 2006) – neural network – discriminant analysis – cluster analysis – Bayes	2 (one-period-ahead-forecast)	– Tree+bagging performs best. – Logistic regression and classification trees perform similarly and outperform the neural network approach, discriminant analysis, cluster analysis, and Bayes. – The models have staying power (i.e. they perform similarly in the second period).
Xie et al. 2009	Marketing	– improved balanced random forest (IBRF) – neural network – classification tree – support vector machines	1	– IBRF outperforms the other three methods.
Zahavi and Levin 1997	Marketing	– Neural network – logistic regression	2 (one-period-ahead forecast)	– The difference in the performance of both methods is rather small. – Neural network approach is complicated.
This study	Marketing	– logistic regression – classification trees – both+bagging	3-4	– Classification tree in combination with bagging has the strongest predictive performance. – Staying power of models is relatively small.

2.2.2 Aggregation methods

To improve the performance of the aforementioned methods predictions could be obtained by averaging the results of a large number of models. The intuition behind aggregating multiple model results is that the quality of a single predictor might depend heavily on the specific sample (Breiman 1996b) and is not known beforehand. Averaging predictors that vary substantially will result in a more stable predictor (Breiman 1996a; Malthouse and Derenthal 2008). Recently, a number of aggregation methods have been introduced in marketing. Malthouse and Derenthal (2008) aggregated predictions based on a large number of cross-sectional models, each of them estimated on a data set from a different moment in time. In their study, the aggregated models outperformed the single models. Another aggregation method originating in the machine learning field is bootstrap aggregation, or bagging, which has been applied by Lemmens and Croux (2006) to model churn of a US wireless telecommunications company. In the bagging procedure a model is estimated on a number of bootstrap samples of the original estimation sample, resulting in a number of predictions for every customer. The final prediction is obtained by taking the average of all predictions (Breiman 1996a). The bagging procedure provided classifiers that were substantially better than those obtained by a single classification tree. Although it might improve the performance of classification trees, bagging might have a negative effect on the performance of the logistic regression model (Perlich, Provost, and Simonoff 2004). Bootstrap samples are random samples of size n drawn with replacement and hence the number of original observations in the bootstrap samples is smaller than in the complete sample. As a result of the smaller effective sample size, the performance of each logistic regression model is likely to be worse. Furthermore, the logistic regression model tends to be less sensitive to the specific sample that is used to estimate the model. Due to less variance in the estimated churn probabilities averaging them will have less effect.

To summarize, aggregating predictors is a simple way to improve the performance of commonly used models. However, bagging the logistic regression might not lead to the expected improvement due to effect of data set size and lower sample sensitivity.

2.2.3 Staying power and model adaptation

So far, all the results we have discussed are based on in-period or one-period-ahead forecasts (see Table 2.1). However, building churn prediction models is a time-consuming and therefore costly operation (Malthouse and Derenthal 2008) and hence it is valuable to assess how well these models perform in the longer term.

To obtain accurate long term churn predictions firms need a good prediction model, producing results that are reliable and generally accepted as such. Little (1970; 1975) proposed five implementation criteria for the structure of good models and one of those criteria is adaptivity. In general, models can be adapted in three ways; re-estimation of the parameters, including or excluding variables from the model, or changing the entire structure. Changing the structure refers to using a different type of model, a different unit of analysis, or modeling a situation that has changed over time, e.g., a sales model of a retailer that setup a new distribution network (Leeflang et al. 2000). The models we analyze in this study are adaptive in the sense that we can re-estimate the model parameters and add or delete variables from the models. We leave the possibility of changing the model structure aside since the aim of this study is to compare the performance of a limited number of models with a fixed structure.

In general one would prefer a churn prediction model with large staying power. Unfortunately, this does not always occur in practice. An important factor is that changes in the market environment (i.e. the competitive setting) might affect customer behavior (Blattberg, Kim, and Neslin 2008, p. 280, Malthouse and Derenthal 2008). As the market environment is typically not included in churn prediction models, these changes will lead to a decrease in staying power, since the previously estimated model no longer matches with the actual situation.

Given that models are adaptive, the question is if, when, and how models need to be adapted. The most important determinant of the need for adaptation is the difference between actual and predicted values of the dependent variable, i.e. the predictive performance over time (Leeflang et al. 2000, p. 108). In particular, the staying power, defined as the predictive performance of a model in a period x months after the estimation period (Neslin et al. 2006), is an important aspect. To assess how a model needs to be adapted, it should be estimated on a number of consecutive periods using a fixed set of variables. By looking at the size, sign, and significance of the parameters one can decide whether the same parameters have to be re-estimated or different variables have to be included in the model.

There are reasons to expect that staying power differs between models in a dynamic environment. Over time, estimation samples change. Especially classification trees seem to be vulnerable to these changes (Breiman 1996a). As the bagging procedure consists of averaging the predictions based on models that have been estimated on a large number of slightly different samples, the in-period accuracy increases, and hence the staying power might increase as compared to the single model case. As we mentioned earlier, the logit model is less sensitive to minor changes in the estimation sample (Perlich, Provost, and Simonoff 2004) and hence classification trees are expected to benefit most from the bagging procedure.

In sum, based on the discussion above we expect that the classification trees will benefit most from the bagging procedure. Furthermore, we expect that the trees in combination with the bagging procedure will outperform the other three methods. However, a limited size of the data set and a low signal-to-noise ratio are in favor of the logistic regression model and might weaken the results.

2.3 DATA

In the empirical study we used two data sets. The first set of data we use is part of a customer database of a large internet service provider (ISP), which is owned by a telecommunications company offering a wide range of services (e.g., fixed phone line subscriptions and digital television). The data set consists of observations for the period January-September 2006, which we divide into four periods of equal length (labeled Q1 to Q4). We include customers with an ADSL connection and exclude out-dated dial-up subscriptions, since the company was actively changing these subscriptions. This forced switching behavior would disturb the analyses. Churners are those customers that have an internet subscription at the beginning of the observation period and have no subscription at the end.

The second data set comes from a health insurance company and consists of yearly churn data of the period 2004-2006. We use yearly data since customers typically switch at most once a year in this industry in the Netherlands. (Dijksterhuis and Velders 2009; Donkers, Verhoef, and De Jong 2007). Churners are the customers that have an insurance at the beginning of the year but do no longer have one at the end of the year.

The variables we include in the models can be divided into two groups: customer characteristics and relationship characteristics (Prins and Verhoef 2007). The first group consists of sociodemographic variables, socioeconomic variables and commitment. The relationship characteristics consist of relationship length, breadth, and depth (Bolton, Lemon, and Verhoef 2004). A brief overview of the link between these predictors and the extant CRM literature is provided in Table 2.2. Please note that we included log-transformed versions of the revenue variable in the ISP data and of the relationship length variable in the insurance data to reduce the skewness of the distribution.

2.4 METHODOLOGY

2.4.1 Sampling

For the ISP data we use two different samples per period: a balanced sample (50%-50% churners-nonchurners) to estimate the models and a proportional random sample to validate the models. All random samples consist of 100K customers; the sizes of the balanced samples are 7063 (Q1), 6967 (Q2), 7146 (Q3), and 7001(Q4).

For the analysis of the insurance data we use balanced samples only; proportional random samples were not available to us. The sizes of those samples are 1789 (2004), 1294 (2005), and 1474 (2006).

We use balanced samples for estimation since the obtained classifiers outperform the ones obtained by random samples (Donkers, Franses, and Verhoef 2003; Lemmens and Croux 2006).

2.4.2 Models

All models are estimated using a fixed set of variables per data set as described in section 2.3[3]. For a detailed description of the logistic regression model, we refer to a statistical textbook (e.g., Franses and Paap 2001). The classification trees are generated using a splitting rule based on the commonly used Gini index of diversity, suggested by Breiman et al. (1984, p. 113). To avoid overfitting of the trees we use the cost-complexity pruning method (Breiman et al. 1984, p. 66).

In the bagging procedure a model is estimated on B bootstrap samples of the original estimation sample, resulting in B different predictions for every customer. The final prediction is obtained by averaging all B predictions (Breiman 1996a). The top-decile lift was used to determine the optimal value of B; we set it equal to 100 in all cases[4] (Lemmens and Croux 2006).

2.4.3 Performance measures

To compare the predictive performance of the various models we use two performance measures. A measure that is commonly used for these types of models is the top-decile lift (TDL; Lemmens and Croux 2006; Malthouse 1999; Neslin et al. 2006). The TDL is defined as the fraction of churners in the top-decile divided by the fraction of churners in the whole set (Blattberg, Kim, and Neslin 2008, p. 263). This measure represents the ability of a model to identify those customers that have a high churn probability, the so-called high risk customers.

Table 2.2: Link between included predictors and CRM literature

Predictors ISP data	*Predictors Insurance data*	*Theory*	*Studies*
		Customer characteristics	
Age, Household size, Move	Age, Family configuration	Sociodemographics	Mittal and Kamakura 2001 Verhoef et al. 2003
Income	Income	Socioeconomics	Mittal and Kamakura 2001 Verhoef et al. 2003
Carrier pre-select (CPS)		Commitment	Gruen, Summers, and Acito 2000; Verhoef 2003
		Relationship characteristics	
Relationship age company, Relationship age ISP	Relationship age company	Length	Bolton 1998
Value added services fixed phone line		Breadth	Bolton, Lemon, and Verhoef 2004
Revenue fixed phone line, Subscription type fixed phone line, Connection speed	Insurance package type, Individually/Collectively insured	Depth	Lemon, White, and Winer 2002 Bolton, Kannan, and Bramlett 2000

The second measure we use is the Gini coefficient, which takes into account the overall performance of the model. This coefficient is frequently used to measure income inequality. Here, we use it to compare the quality of a model-based selection with a random selection of customers. We calculate the Gini coefficient by dividing the area between the cumulative lift curve and the 45-degree line by the area under 45-degree line (Blattberg, Kim, and Neslin 2008, p. 319)[5].

2.5 EMPIRICAL RESULTS

2.5.1 ISP data

2.5.1.1 Staying power: top-decile lift

Figure 2.1 shows the average top-decile lifts of the four different models. The results have been aggregated across estimation periods for the sake of clarity. The estimation period is denoted by t. The ability of the estimated models to correctly identify high risk customers is decreasing over time, since all lines are downwards sloping. A substantial decrease in period t+2 can be observed. Furthermore, the figure shows that the classification trees outperform the logit models in this respect, because both the line of the tree model and the line of the tree+bagging model are above the lines of the logit model. With respect to the effect of applying a bagging procedure, the following can be observed. The logit model does not benefit from this procedure, since both lines overlap in Figure 2.1. However, the bagging procedure improves the predictive performance of the classification tree substantially. Both for the in-period and one-period-ahead predictions the TDL is higher for the tree in combination with a bagging procedure than for the single tree.

2.5.1.2 Staying power: Gini coefficient

In Figure 2.2 the average Gini coefficients of the four models are shown. Similar to what we found for the top-decile lift, the overall performance of all models decreases over time, indicated by the downwards sloping lines. Again, the tree models outperform the logit models and the bagging procedure improves the predictions of the classification trees but has little effect on the logit model results.

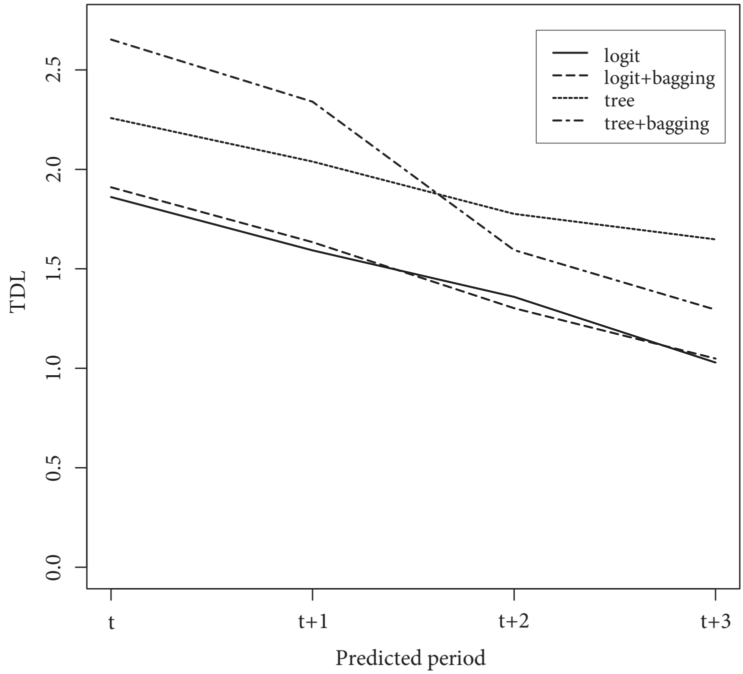

Figure 2.1: Average top-decile lifts of models estimated at time t (ISP data)

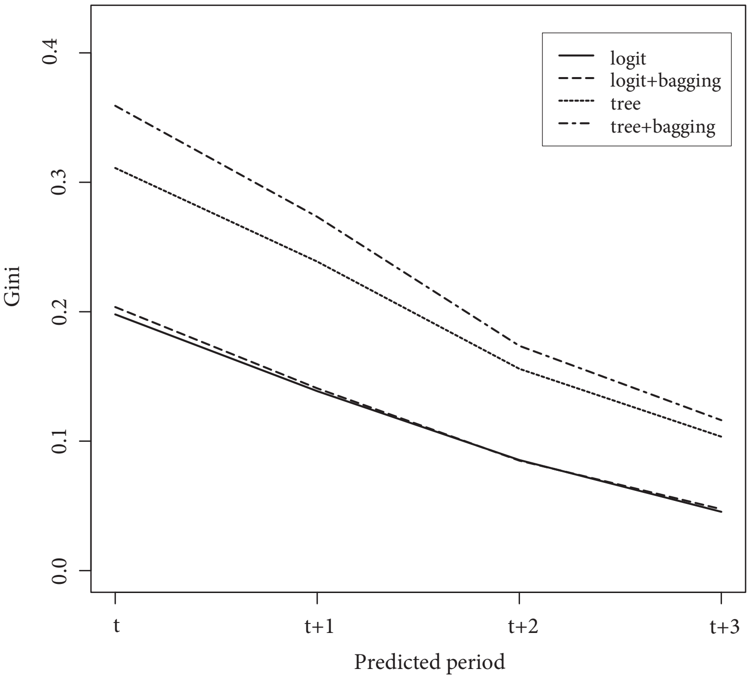

Figure 2.2: Average Gini coefficients of models estimated at time t (ISP data)

2.5.1.3 Parameter assessment

In Table 2.3 the parameter estimates of the single logit models are presented for each estimation period. The most important observation is that the significance and size of the parameter estimates change over time. Only 4 of the 25 variables (16%) have a significant effect on churn in all periods. None of these four effects changes in sign. Customers with a higher revenue on their fixed phone line have a higher probability to churn on their internet subscription and those with the cheapest fixed phone subscription (type 1) have a higher churn probability than those with a more expensive subscription. Customers that used carrier pre-select (CPS) in the past have a higher probability to churn and older people (age ≥ 65) have a lower churn probability than young people. Three additional variables have a significant effect of the same sign in three of the four periods and four variables have a significant effect in the same direction in only two periods. There are five variables that have a significant effect only in Q1, where the sign of the effect mostly stays the same in the subsequent periods though the effect is no longer significant. Finally, the effects of two variables, relationship age ISP and connection speed medium are significant in Q1 and Q3, but the sign of the effects is opposite in the two periods; in Q1 the effect is positive, in Q3 it is negative, which clearly indicates low parameter stability.

The results of the logit model in combination with a bagging procedure are very similar to those of the single logit model. The parameter estimates show very little variation over the 100 bootstrap samples. Hence, we do not present them here.

Table 2.4 shows the splitting variables of the single classification trees for all four periods. The results show that relationship ISP, connection speed, and age (33% of the variables) appear in all trees. Two of these variables, namely connection speed and age, appear in all logit models and all trees and can thus be considered important predictors of churn here. In contrast with the logit results, the variable value added services does not play a role in the classification tree in Q2.

A summary of the results of the classification trees in combination with a bagging procedure is provided in Figure 2.3. A large diversity in the frequencies can be observed, indicating that most variables are used only in a subset of all the bootstrap samples. This corresponds to the notion of instability with respect to the estimation sample. Two variables (20%), relationship age ISP and connection speed, have a stable effect on churn, since they appear in nearly all the trees in all periods.

Table 2.3: Parameter estimates of the single logit model (ISP data)

Variable	*Period*			
	Q1	Q2	Q3	Q4
Revenue fixed phone line (€)	0.1038**	0.1605**	0.1097**	0.1248**
Carrier pre-select	0.1608*	0.4869**	0.5716**	0.3507**
Relationship age company (months)	0.0000	-0.0007**	-0.0010**	-0.0012**
Relationship age ISP (months)	0.0084**	0.0009	-0.0019*	0.0001
Connection speed (ref. cat. 'slow')				
medium	0.7834**	0.0199	-0.5348**	-0.1809*
high	0.8992**	0.3996**	-0.1658	-0.1195
Fixed phone subscription (ref. cat. 'standard')				
Type 1 (cheapest)	0.7715**	1.0344**	0.9207**	0.4580**
Type 3	-0.2412**	-0.1509*	-0.0198	0.0340
Type 4	-0.2957**	-0.0438	-0.1181	0.0846
Type 5	-0.4219**	-0.2906*	0.1256	0.1229
Household size (ref. cat. '3')				
1	-0.3177**	-0.1016	-0.1293	-0.1103
2	-0.1597*	-0.0426	-0.0191	-0.0756
4	0.0132	-0.0853	-0.1349	-0.0796
5	0.3009**	0.1406	-0.0562	0.0100
> 6	0.1219	0.0628	-0.2390	-0.3527*
Age (ref. cat. '25-35')				
< 25	0.0626	-0.0240	-0.1151	0.2874*
35-45	0.0909	0.0048	-0.1234	-0.0112
45-55	0.1169	0.0947	-0.0257	-0.0088
55-65	-0.2477**	-0.2320*	-0.1511	-0.1338
>= 65	-0.4017**	-0.2286*	-0.3038**	-0.3023**
Income (ref. cat. '1.5 times standard')				
< standard income	0.2101	0.2119*	0.3205**	0.4043**
standard income	0.0757	0.1762*	0.1109	0.3189**
2 times standard income	0.0094	-0.1038	-0.0048	0.0173
> 2 times standard	-0.2028**	-0.2498**	-0.2147**	-0.0876
Value added services fixed phone line	-0.0057	-0.1553*	-0.0476	-0.0603

*p<0.05

**p<0.01

Table 2.4: Splitting variables in the estimated classification trees (ISP data)

Variable	*Period*			
	Q1	Q2	Q3	Q4
Revenue fixed phone line		x		
Carrier pre-select (CPS)			x	
Relationship age company	x		x	x
Relationship age ISP	x	x	x	x
Connection speed	x	x	x	x
Fixed phone subscription	x	x	x	
Household size	x			
Age	x	x	x	x
Income	x			
Value added services fixed phone line				

x : variable has been used as splitting variable in the tree

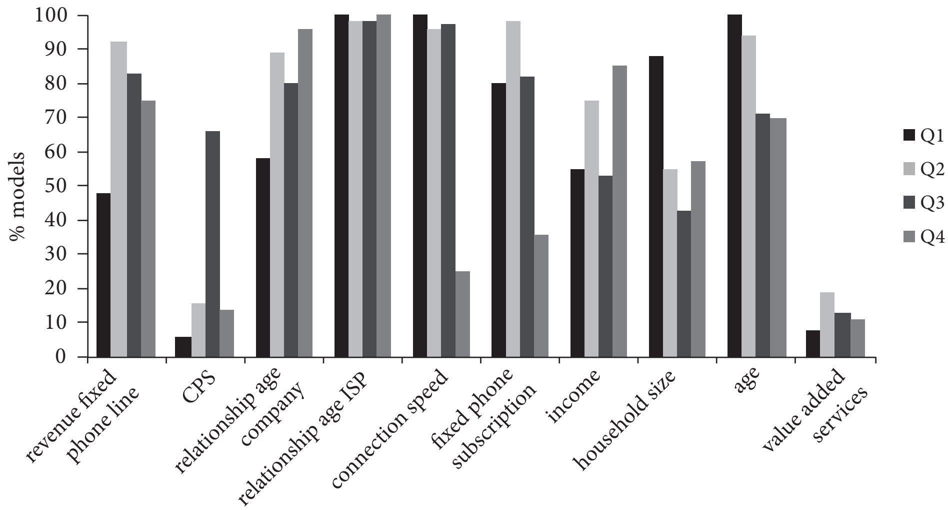

Figure 2.3: Fraction of the 100 classification trees in the bagging procedure in which variables are used as a splitting variable (ISP data)

2.5.1.4 Model variability

There are three possible explanations for the changes in the models that we estimate: multicollinearity, omitted variables, and actual changes in the situation that we model. To check whether the data suffers from multicollinearity we calculated the condition indices. All indices are smaller than 32 (they range from 1 to 21) and hence there is no severe problem with multicollinearity (Gujarati 2003, p. 361). With respect to the omitted variable problem we acknowledge that we do not take information like the market environment and customer attitudes into account. However, we argue that we included all variables that are both relevant in this situation and very common in database marketing studies, see Table 2.2. Therefore, the most plausible explanation is that the situation that we model changes over time due to changes in the environment (i.e. increasing price competition). These environmental changes cannot be included in standard churn models, which predict churn at a specific point in time using database data. For that purpose dynamic churn models should be developed (Leeflang et al. 2009).

2.5.2 Insurance data

2.5.2.1 Staying power: top-decile lift

Figure 2.4 shows the average top-decile lifts of the four different models. We again aggregated the results for the sake of clarity. As was the case for the ISP data the lines are downward sloping except for the tree-line between t+1 and t+2. A possible explanation could be that the model is too simple and captures only a few main effects, since the model performs the worst in period t and t+1, but performs slightly better than the other models in t+2. With respect to applying the bagging procedure we again observe that the logit models do not benefit, since the two lines overlap in Figure 2.4. However, the predictive performance of the classification trees improves due to the bagging procedure. Both in period t and t+1 the line of the tree in combination with a bagging procedure is above the line of the single tree.

2.5.2.2 Staying power: Gini coefficient

In Figure 2.5 the average Gini coefficients of the four models are depicted. Here, a steep decrease can be observed between period t and t+1, which indicates a substantial decrease in overall model performance. After reaching a rather low level of about 0.05 the curve flattens out between t+1 and t+2. Apart from the shape of the decrease the findings are similar to what we found for the top-decile lifts.

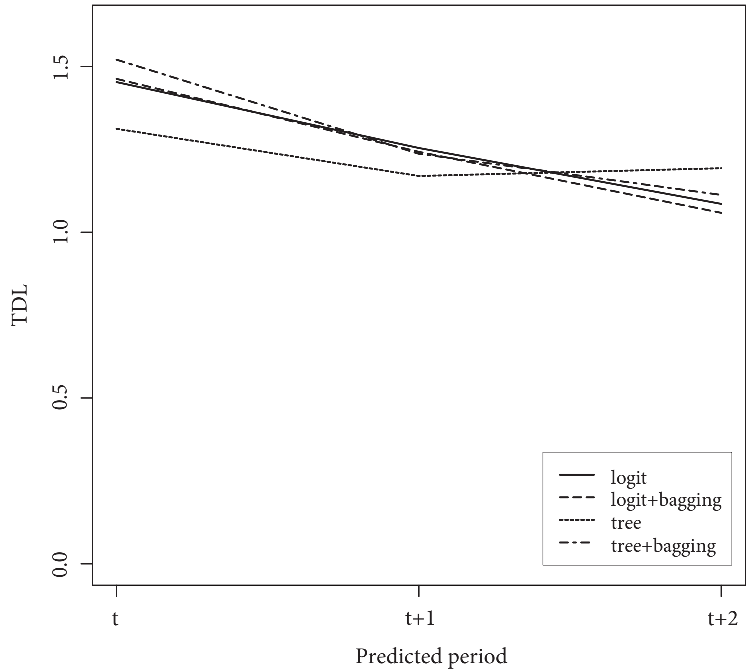

Figure 2.4: Average top-decile lifts of models estimated at time t (insurance data)

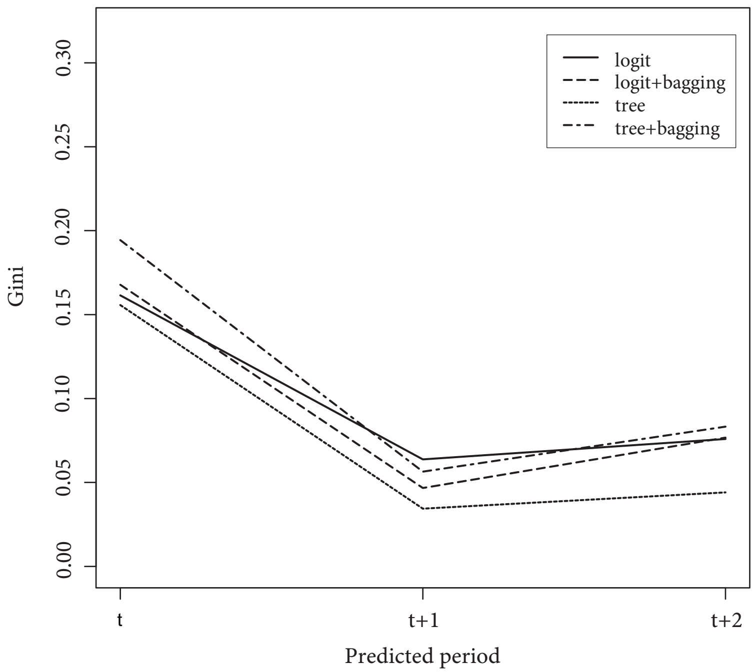

Figure 2.5: Average Gini coefficients of models estimated at time t (insurance data)

2.5.2.3 Parameter assessment

The parameters of the single logit models are shown in Table 2.5. The sign, size, and significance of the estimates vary substantially over time. Only one of the parameters is significant in all three periods; the unknown family configuration group has a higher probability to churn than customers from the other groups. Three parameters (13%) are significant and have the same sign in two periods. Age, relationship length, and the moving indicator all have a negative effect on churn. Furthermore, five parameters have a significant effect in only one period. Finally, three of the package type dummies have a significant effect on churn in two periods. However, the effect is negative in 2004 and positive in 2006. Again, this illustrates the low parameter stability of the model.

Table 2.6 shows the splitting variables of the classification trees for all three periods. The results show that only one variable (age) is used as a splitting variable in all three periods. This variable had a significant effect in the logit model for two out of the three periods and can hence be considered as a relatively important predictor of churn. Furthermore, four of the variables appear in only one of three trees.

In Figure 2.6 a summary of the classification trees in combination with the bagging procedure is provided. As was the case for the ISP data, a large diversity in the frequencies can be observed. Moreover, in this case none of the variables appears in a large proportion of the trees in all periods.

2.5.2.4 Model variability

Likewise as in the ISP case, there are three possible explanations for the changes found in the estimated models. Again, we have no reason to believe that the data suffers from severe multicollinearity; all condition indices are well below 32 (range from 1 to 12). Like in the ISP case we include commonly used predictors in churn models. We suspect that the changes in the model mainly occur due to changes in the environment, which are again not captured in the currently used churn models. Again this would pledge for the inclusion of more dynamics in churn models, which is currently not done.

Table 2.5: Parameter estimates of the single logit models (insurance data)

Variable	*Period*		
	2004	2005	2006
Age (years)	-0.0104**	-0.0004	-0.0144**
Relationship length (years)	-0.3625**	-0.2248**	-0.1116
Package type (ref. cat. '0')			
1	0.0955	0.8462	-0.5464
2	-0.0216	0.4145	0.5371
3	-0.7110**	-0.2046	0.2680
4	-0.9320**	-0.1590	0.2495
5	-0.9182**	-0.2868	0.6868*
6	-0.8702**	-0.2811	0.5635*
7	-0.9738**	-0.0779	0.7244*
8	-1.1030**	0.1386	0.4352
Family configuration (ref.cat. 'single')			
no kids	0.1086	-0.1515	0.8324**
kids	0.1337	-0.0048	-0.3571
family1	-0.1053	-0.3456	0.3325
family2	0.2331	0.0938	0.2395
unknown	0.6019**	0.3903**	0.9138**
Income (ref. cat. 'unknown')			
> 2 times standard	0.3756	0.0737	-0.0448
standard-2 times standard	-0.0415	0.0770	0.1938
standard income	-0.0917	0.0553	-0.2693
minimum-standard income	-0.1248	-0.0318	-0.4017*
minimum	0.0497	-0.0822	-0.7447*
variable	-0.3054	-0.1121	0.0525
Collectively insured	-0.1912	-0.1767	-0.4183*
Moved	-3.7922**	-0.0730	-0.5359**

*p<0.05

**p<0.01

Table 2.6: Splitting variables in the estimated classification trees (insurance data)

Variable	*Period*		
	2004	2005	2006
Age	x	x	x
Relationship length	x	x	
Moved	x		
Package type			x
Family configuration			x
Income		x	
Collectively insured			

x : variable has been used as splitting variable in the tree

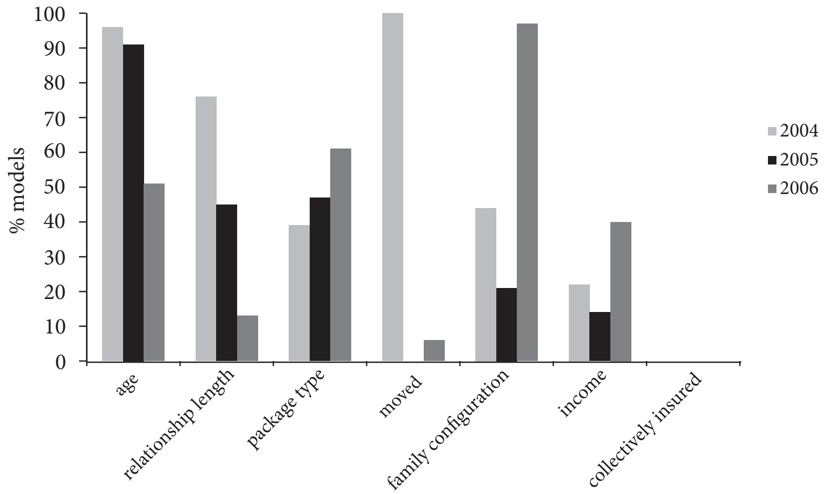

Figure 2.6: Fraction of the 100 classification trees in the bagging procedure in which variables are used as a splitting variable (insurance data)

2.6 CONCLUSION

In this chapter, we contribute to the existing literature on churn prediction models by studying the staying power of frequently used and well-performing prediction models. Furthermore, we tested the predictive performance of frequently used methods (i.e. logistic regression, trees, bagging) in two industries. Specifically we analyzed customer data of an ISP and a health insurance company. We evaluated the results of a logistic regression model, a classification tree, and of both in combination with a bagging procedure estimated on a number of consecutive periods.

The general conclusions of our model comparison are as follows:

- Confirming prior studies (i.e. Lemmens and Croux 2006) our study shows that overall classification trees combined with a bagging procedure provide the best predictive performance for all studied time periods. These findings are stronger for the ISP data which is probably due to the size of the data sets; trees tend to perform better on larger data sets (Perlich, Provost, and Simonoff 2004).
- The predictive quality of the investigated models declines over time. A substantial decrease in predictive quality is found in period t+2 for the ISP data and in period t+1 for the insurance data. This indicates that the staying power of these models is very limited.
- Although the bagging procedure improves the predictive power of classification trees, there is no strong evidence that this procedure improves the staying power. The predictive performance declines similarly for all studied models.

The limited staying power of the models implies that models cannot be used for a long time period in these specific settings. Both studies indicate that a churn model should be used for a maximum of one period subsequent to the estimation period; for the prediction of churn in period t+2 new models should be built. Simply updating a churn prediction model will not be sufficient to obtain reliable estimates; the model building procedure should start with selection of the important variables. The benefits of this new model development are substantial. In our empirical studies, using a more recent model leads on average to an increase of 20% in the number of churners in the predicted top-decile.

The limited staying power of the studied churn prediction models illustrates that assuming a constant churn probability for CLV calculations is a risky strategy; churn predictions and hence CLV predictions become very unreliable in the longer term. This is in line with the findings of Malthouse and Blattberg (2005) This can potentially have strong implications for CLV-based marketing resource allocation strategies (Donkers, Verhoef, and De Jong 2007; Venkatesan and Kumar 2004; Zeithaml, Rust, and Lemon 2001). Our results suggest that these allocation models should also be updated regurlarly.

The need for regular re-estimation illustrates the importance of automation of the modeling process; this would increase the model building efficiency and thus lower the costs. However, the estimation procedure is complicated by the required variable selection. Therefore, to automate the churn modeling process, implementation of advanced model building tools is essential.

2.7 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Although we are confident with the results, it remains unclear whether they are generalizable over a broader range of services than the two we studied. Therefore, it would be interesting to validate our findings on customer databases of other services. This would reveal whether the limited staying power and the instability of the parameters is typical for the industries studied or whether these findings hold for other service sectors as well. Unfortunately, we did not have access to such data sets.

A second valuable extension of this study would be to analyze more periods than the maximum of four we used. A longitudinal data set containing a large number of periods would allow us to estimate time-varying parameters and possibly seasonality effects. It could be the case that there exists a certain pattern in the churn behavior of customers that could only be observed over a longer time period consisting of at least multiple years of data.

One additional avenue for further research is the development of more dynamic churn prediction models. The currently used models are not suited for the inclusion of dynamic changes in the customer base, market environment etc. in the model. This may explain why the parameter estimates of our studied models are not stable over time. We therefore urge researchers to take a next step in churn modeling and to develop models that include more dynamics (see also Leeflang et al. 2009).

Finally, our results indicate that the predictive performance of models depends on the characteristics of the data. Hence, more research is needed within marketing to assess under what circumstances different types of prediction models perform best.

Chapter 3

Dynamic Effects of Social Influence and Marketing on the Adoption of High-Technology Products¶

3.1 INTRODUCTION

The effectiveness of traditional marketing instruments has declined in many markets, whereas the effects of social interactions between consumers on buying behavior and the opportunities to exploit them have increased (Sethuraman, Tellis, and Briesch 2011; Van den Bulte and Wuyts 2007). As a result, marketers have shown renewed interest in the effects of social influence on customer behavior (Kumar, Petersen, and Leone 2007; Van den Bulte and Wuyts 2007). However, these developments also pose new challenges for marketing researchers and practitioners (Godes and Mayzlin 2004; Libai et al. 2010; Stephen and Galak 2010; Trusov, Bucklin, and Pauwels 2009). Now that there is consensus in the literature that social influence affects behavior in customer relationships, we need insights into the factors that affect social influence (Iyengar, Van den Bulte, and Choi 2011). This study investigates the dynamics of the impact of social influence and the interaction between social influence and direct marketing.

We analyze social influence among customers of a mobile telecommunications operator using adoption data of a high-technology product. We define social influence on adoption as the influence of related others on a person's adoption probability. More specifically, the social influence effect is the effect of an adoption among a customer's

¶ This chapter is based on Risselada, Hans, Peter C. Verhoef, Tammo H.A. Bijmolt (2011), "Dynamic Effects of Social Influence and Marketing on the Adoption of High-Technology Products," working paper, University of Groningen contacts in month t-1 on the customer's adoption probability in month t. Table 3.1 provides a selective overview of the extant literature on the role of social influence in the adoption process. Prior research reveals a positive effect of social influence on adoption in multiple industries, including telecommunications (Hill, Provost, and Volinsky 2006), online retailing (Bell and Song 2007; Choi, Hui, and Bell 2010), and pharmaceuticals (Iyengar, Van den Bulte, and Valente 2011). However, although studies on this main effect of social influence provide valuable insights, several issues remain relatively unexplored.

First, most studies assume that social influence effects are constant over the time (see Table 3.1). Only recently have researchers included time-varying parameters of social influence in their models (Bell and Song 2007; Chen, Wang, and Xie 2011; Choi, Hui, and Bell 2010). These studies provide some initial evidence for a decreasing effect of social influence. Chen, Wang, and Xie (2011) suggest that this is due to information substitution dynamics; that is, as more common knowledge and general information become available over time, information obtained through social contacts becomes less important. Findings of several diffusion studies are consistent with this decreasing social influence effect (Easingwood, Mahajan, and Muller 1983; Van den Bulte and Lilien 1997; Van den Bulte and Stremersch 2004). In this study, we allow the effect of social influence to vary over time.

Second, an important but understudied issue is the role of marketing versus the role of social influence in driving behavior in customer relationships. Prior research in customer management has frequently examined the effects of direct marketing communication on behavior in customer relationships (e.g., Prins and Verhoef 2007; Venkatesan and Kumar 2004; Verhoef 2003). These studies, however, ignore the role of social influence. Similarly, studies on social influence have frequently ignored the role of marketing, which might cause the effects of social influence to be biased upward because of so-called correlated effects (Manski 2000; Van den Bulte and Lilien 2001). In the same vein, the found effects of marketing in customer management might also have been biased. Therefore, it is important to study marketing and social influence effects simultaneously. Only two studies, both in a pharmaceutical context, have examined marketing and social influence effects at the individual level. Iyengar, Van den Bulte, and Valente (2011) find positive effects for both, and Manchanda, Xie, and Youn (2008) show that the effect of detailing is most important in the first four months after product introduction, but thereafter the effect of social influence dominates. However, the latter study is being criticized on two issues, (1) the study suffers from a truncation bias, as shown by Van den Bulte and Iyengar (2011), and (2) the relevant network of an individual is determined by an arbitrary distance measure.

Table 3.1: Selection of relevant literature on social influence and adoption

Study	*Category*	*Adoption/ Adoption Timing*	*Social Influence Parameter*	*Marketing*	*Definition of Network*	*Main Findings*
Hill, Provost, and Volinsky 2006	Telecommunication service	Adoption	Constant	No	Mobile phone graph	– Network neighbors are more likely to adopt. – Models significantly improved by incorporating network information.
Manchanda, Xie, and Youn 2008	Pharmaceuticals	Adoption timing	Constant	Yes	Geographic proximity	– Marketing and social influence affect adoption (at the individual level). – Role of contagion dominates marketing from fourth month onward.
Van den Bulte and Lilien 2001	Pharmaceuticals	Adoption timing	Constant	Yes	Self-reported	– When marketing efforts are controlled for, contagion effects disappear. – Article underscores the importance of controlling for confounds when studying the role of social contagion.
Iyengar, Van den Bulte, and Valente 2011	Pharmaceuticals	Adoption timing	Constant	Yes	Self-reported	– Contagion operates over network ties. – Peer's usage is more important than adoption. – Self-reported leaders and sociometric leaders tend to adopt early. – Heavy users adopt early. – Self-reported leadership and sociometric leadership are only moderately correlated. – Self-reported leaders are less sensitive to social influence.
Iyengar, Van den Bulte, and Choi 2011	Pharmaceuticals	Adoption timing	Constant	Yes	Self-reported + zip code	– Evidence for two social processes: social learning and normative legitimation.
Bell and Song 2007	Online retailer	Adoption timing	Constant	No	Zip code	– The neighborhood effect is significantly positive and economically meaningful.

Study	*Category*	*Adoption/ Adoption Timing*	*Social Influence Parameter*	*Marketing*	*Definition of Network*	*Main Findings*
Choi, Hui, and Bell 2010	Online retailer	Adoption timing	Time varying	No	Zip code	– Proximity effect is strong in early stages. – Similarity effect becomes more important with time.
Aral, Muchnik, and Sundararajan 2009	Service application adoption	Adoption	Time varying	No	Online social network	– Homophily explains more than half the perceived behavioral contagion. – Methods other than the matched sampling approach overestimate peer influence by as much as 300%–700%.
Du and Kamakura 2011	Consumer goods	Adoption timing	Constant	Yes	Zip code	– The influencer groups is individual, product, and time specific. – Firms should target innovative and influential customers first.
Katona, Zubcsek, and Sarvary 2011	Online social network membership	Adoption timing	Constant	No	Online social network	– Density of connections is positively related to influence. – Size is negatively related to social influence. – Significant effects of influencer and adopter characteristics.
Nam, Manchanda, and Chintagunta 2010	Video on demand	Adoption timing	Constant	Yes	Zip code	– Asymmetric effects; effect of negative word of mouth is twice as large as that of positive word of mouth.
This study	Smartphones	Adoption timing	Time varying	Yes	Mobile call graph	

An important issue is whether marketing and social influence strengthen each other, function as substitutes, or have independent effects on adoption. In the first situation, synergy effects between social influence and marketing may be present, as has been shown in the effects of different advertising instruments (Naik and Raman 2003). However if social influence and marketing function as substitutes, firms could reallocate marketing budgets from, for example, (direct) advertising to social network marketing (i.e., viral marketing campaigns).

This discussion leads us to posit the following two research questions: (1) How do the relative effects of social influence and marketing develop from the product introduction onward? and (2) Do social influence and marketing strengthen each other in driving customer adoption behavior, or do they function as substitutes? We use individual-level data on smartphone adoption, customer characteristics (e.g., service usage, gender), direct marketing efforts, and call detail records (CDR) of a random sample of customers of a Dutch mobile telecommunications operator. We analyze the time-varying effects of social influence and marketing on individual adoption behavior while controlling for tie strength. Furthermore, we investigate whether social influence and marketing interact. We use a hazard model with a fractional polynomial approach to incorporate time-varying parameters (Berger, Schäfer, and Ulm 2003; Royston and Altman 1994). The results show that (1) the effect of social influence decreases from the product introduction onward, (2) the effect of direct marketing is positive and constant and dominates the effect of social influence from the fifth month since product introduction onward, and (3) there is no significant interaction effect between social influence and direct marketing on adoption behavior.

The study contributes to the marketing literature on social influence and adoption in three ways. First, we analyze the time-varying effects of social influence on adoption in consumer markets. Second, we compare the effects of marketing and social influence from the product introduction onward. Third, we empirically investigate the potential interactions between social influence and direct marketing. In doing so, we shed more light on an important discussion − whether the increasing prevalence of social networks in consumer decision making leads traditional marketing efforts to become superfluous or, at a minimum, less effective. This study also contributes to the literature on customer management. Existing models consider individual customers independent, affected only by firm efforts (e.g., service quality, direct marketing) (Bolton, Lemon, and Verhoef 2004; Venkatesan and Kumar 2004). Recently, scholars have called for more attention on customer engagement and specifically network effects that influence customer behavior and value (e.g., Kumar et al. 2010; Libai et al. 2010; Van Doorn et al. 2010). This study is among the few studies that examine both network effects and direct marketing effects on behavior in customer relationships.

The remainder of this chapter is structured as follows: We begin by describing our conceptual model and formulating our hypotheses. We then present our data and elaborate on the econometric model, before providing an overview of the results. Finally, we discuss the main findings and offer management implications and study limitations.

3.2 CONCEPTUAL MODEL AND HYPOTHESES

After a product launch, consumers must do at least three things before adoption. First, they must become aware of the product's existence. Second, they need to appreciate the potential benefits of the new product. Third, they need to decide to actually adopt the product. Consumers acquire information from different sources beyond the firm that launches the product, one of which is other consumers, who also can persuade the consumer to adopt the product (Kiel and Layton 1981; Murray 1991; Rogers 2003). Therefore, we consider the role of both other consumers and the firm in developing our theoretical framework. In line with the customer management literature, we focus on the factors that differ among individual customers. First, we discuss the role of the other consumers in the ego network of a consumer, and second, we discuss the role of direct marketing.

A consumer communicates with other consumers in his or her ego network and has a relationship with them. We refer to this group as related others. This relationship allows for the exchange of information about a new product. We refer to all other consumers in the market as unrelated others. Consumers do not communicate with them but can observe their behavior.

An instrument that firms commonly use to reach individual consumers is direct marketing. The main goal of this instrument in an adoption setting is to persuade consumers to adopt a new product. This call for action can be a special offer or a specific piece of information that is particularly relevant to a consumer at a certain moment (Prins and Verhoef 2007; Rust and Verhoef 2005; Venkatesan and Kumar 2004).

In this study, we model the adoption of a high-technology product for which we take into account both sources of influence discussed above. Figure 3.1 depicts our conceptual model. The dependent variable is adoption of individual i at time t. We include two main antecedents of adoption in the model: (1) network variables and (2) direct marketing. Beyond that, we control for the role of sociodemographics, and relationship characteristics (e.g., Arts, Frambach, and Bijmolt 2011; Prins and Verhoef 2007). We infer social influence on adoption in month t from the effect of an adoption in month t-1 in the ego network of the customer. We also account for the effects of other network variables, such as tie strength and homophily. Homophily is the tendency of people to connect with similar others (e.g., Nitzan and Libai 2011; Van den Bulte and Wuyts 2007). We include a function of time to account for the factors that affect all consumers in the market, such as the total number of adopters in the market and mass marketing by the firm. To account for potential time-varying effects, we allow the parameters of social influence and direct marketing to vary over time. Furthermore, we include an interaction effect between direct marketing and social influence to account for potential synergy effects between them. We derive our hypotheses on these effects in the subsections below.

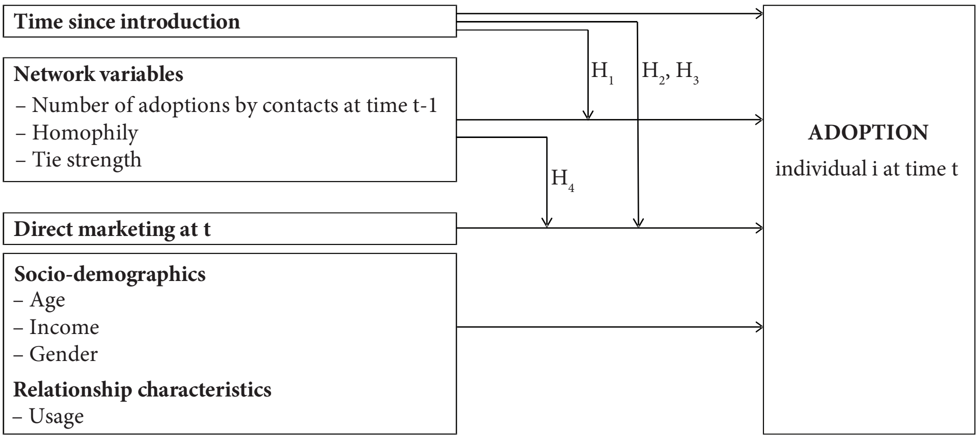

Figure 3.1: Conceptual model

3.2.1 Dynamics

Multiple studies in marketing have shown that the effects of marketing actions may vary over time and/or during the product life cycle (e.g., Ataman, Van Heerde, and Mela 2010; Leeflang et al. 2009; Osinga, Leeflang, and Wieringa 2010; Van Heerde, Srinivasan, and Dekimpe 2010). However, dynamics are typically ignored in the analysis of social influence. There are several arguments for a change in the effect of social influence from the product introduction onward.

The first argument is that the number of adopters in the market is increasing over time. From this larger number of adopters, the norm of adoption is becoming stronger (Bass 1969). According to the theory of information cascades, consumers who have not yet adopted in later stages will rely more on the observation that many others have already adopted and less on the private information they acquire (Bikhchandani, Hirshleifer, and Welch 1998). Assuming that the effect of an adoption in the ego network of a customer is mainly driven by the exchange of information, this implies a decreasing effect of social influence (from related others) from the product introduction onward.

The second argument that is likely to affect the impact of social influence is that knowledge about the product is accumulating. Consumers know little about a product immediately after the launch. In this stage, any additional information consumers can acquire is extremely valuable. This holds true particularly for the information from related others because they, and thus the information they provide, are perceived as more trustworthy than firms (Murray 1991). The knowledge about the product in the market is increasing over time, thus reducing the importance of other information sources, including adopters among related others (Chen, Wang, and Xie 2011). This so-called information substitution dynamic implies a decreasing social influence effect from the product introduction onward.

These two arguments both point to a decreasing effect of social influence from the product introduction onward. However, we might also argue in favor of an increasing effect of social influence, based on heterogeneity among consumers; consumers who adopt early differ from those who adopt later. Those who adopt early tend to be more involved with and have more knowledge about the product than those who adopt later (Mahajan, Muller, and Srivastava 1990). These later adopters might be more uncertain about the adoption decision and perceive greater risks associated with adoption. Therefore, they might benefit more from the information of related others (Chen, Wang, and Xie 2011), which suggests a potential increasing effect of social influence from the product introduction onward. However, these greater risks can also be reduced by the increasing presence of the new product in the market.

Some initial evidence exists for a decreasing effect of social influence from the product introduction onward. Chen, Wang, and Xie (2011) show that the impact of customer reviews on online sales is decreasing. Choi, Hui, and Bell (2010) find that adopters' influence on geographically close others is stronger mainly in the first few months after the product launch. On the basis of these theories and initial empirical evidence, we hypothesize the following time-varying effects of social influence:

H_1: The effect of social influence on adoption (a) is positive and (b) decreases from the product introduction onward.

3.2.2 Direct marketing

Several studies have shown that direct marketing affects individual behavior in customer relationships, such as the adoption of new products (Hill, Provost, and Volinsky 2006; Prins and Verhoef 2007; Venkatesan and Kumar 2004). We therefore assume a positive effect of direct marketing on adoption. Thus far, researchers in customer management have ignored time-varying effects of direct marking. With information substitution dynamics, we might expect that the effect of marketing is decreasing from the product introduction onward because marketing is an information source. However, the role of direct marketing is mostly persuasive. It is a call for action because it contains an offer or tailored information that is particularly relevant to the consumer (Godfrey, Seiders, and Voss 2011; Prins and Verhoef 2007). This call for action should provide the right information to the right customer at the right time, inducing adoption of the new product. Given the clear role of direct marketing as a persuasive behavior focused instrument and the fact that the information and the size of the offer may be adapted to the situation, we hypothesize the following:

H_2: The effect of direct marketing on adoption is (a) positive and (b) constant from the product introduction onward.

3.2.3 Direct marketing and social influence

Firms may aim to benefit from social influence using, for example, viral marketing campaigns (e.g., Hinz et al. 2011; Van der Lans et al. 2010). Thus, social influence may function as a substitute for traditional marketing, and marketing resources may be reallocated to new marketing tactics focusing on social influence (Van den Bulte 2010). Insights are required into the relative effectiveness of alternative marketing tools.

In the early stages of the product life cycle, little is known about the product, and the adoption decision is perceived as risky. Therefore, trustworthy information obtained from related others is of great importance in this stage. Because of the scarcity of knowledge among consumers, the effect of this influence is likely to be stronger than the persuasive effect of direct marketing. Prior research on this issue is greatly limited. Some work has shown that interpersonal communication is the most important source of information in the adoption process (Kiel and Layton 1981; Price and Feick 1984). However, these studies are survey based, and therefore the shortcomings of self-reported data apply. For example, respondents may easily overestimate the effects of social influence and underestimate the effects of marketing (Van den Bulte 2010). Despite this, based on our rationale and the previously hypothesized dynamics of the social influence and direct marketing effects, we formulate the following hypothesis:

H_3: The effect of social influence on adoption is stronger than the effect of direct marketing in the early stage of the product life cycle.

For budget allocation, information is required on the possible synergies between various marketing tools, next to the relative effectiveness of each tool. Although the interaction between social influence and marketing has received limited attention (Libai et al. 2010), research has found positive interactions between the different elements of the marketing mix (Naik and Raman 2003; Naik, Raman, and Winer 2005; Narayanan, Desiraju, and Chintagunta 2004).

Given that social influence has an informative role, it is possible that direct marketing becomes more effective in the presence of social influence. Consumers who are influenced by related others are better informed and thus more capable to judge and appreciate the offer from the firm that should persuade them to adopt. This rationale implies a positive interaction, or a synergy, between social influence and direct marketing.

However, a negative interaction could also occur between direct marketing and social influence. Consumers trust and appreciate the advice from related others, which positively affects their adoption probability. Thus, when the firm interferes by means of an offer or personalized information, the consumer might perceive this as intrusive, which reduces the effect of social influence (Godfrey, Seiders, and Voss 2011). Prior research has found similar negative interaction effects between mass marketing and direct marketing (Prins and Verhoef 2007). This rationale implies a negative interaction between direct marketing and social influence.

Research on the specific interaction between (direct) marketing and social influence is scarce, but two studies have investigated closely related issues. Keller and Fay (2009) analyze possible synergies between mass-media advertising and word of mouth and show that conversations that refer to advertising lead to greater purchase intentions. Stephen and Galak (2010) find a similar effect but argue for a different underlying mechanism. They argue that a continuous stream of online word of mouth activity increases mass-media attention to a product, which in turn positively affects sales. Despite these differences from our study, these initial findings together with our theoretical argument lead us to formulate the following hypothesis:

H_4: Social influence increases the effect of direct marketing on adoption.

3.3 DATA

We examine consumer adoption of an innovative product – namely, the smartphone, with either a physical or a touch screen QWERTY keyboard, such as the Blackberry and the iPhone (Manes 2004). These mobile phones are innovative because they are fundamentally different from previous generations of mobile phones. That is, they were developed for multimedia applications, online communication, and web browsing. Smartphones are high-technology products and relatively expensive. Therefore, social interactions are likely to influence the adoption decision (Chen, Wang, and Xie 2011). We use individual customer data of a large, random sample of customers of a Dutch mobile telecom operator (n = 15,708).

The dependent variable is time of adoption, and we define it as the number of months between adoption and the moment of introduction by the cooperating telecom operator (April 2007). In the observation period (April 2007–September 2009), 4148 customers (26%) adopted a smartphone. All customers remained until the end of the observation period, and thus 74% of the observations are censored. These censored observations are included in the estimation sample to avoid problems with spurious duration dependence (Van den Bulte and Iyengar 2011). Figure 3.2 shows the empirical hazard function. Adoption data are available only for customers and their contacts who are also customers of the company; the market share of the company was around 45% in that period.

Figure 3.2: Empirical hazard function

3.3.1 Adopter characteristics

The time-dependent covariates consist of monthly observations from the period April 2007 to September 2009. The time-dependent direct marketing variable is a stock variable that indicates how many direct marketing actions (i.e., e-mail, text message, or bill supplement) a customer received in the last four months. We obtained the customer and relationship characteristics, gender, age, income, and usage for each customer. Gender and age are based on the information from the contract and therefore available on the individual customer level. The income variable is a zip code level estimate of the household income as provided by an external data provider. The usage variable is based on the average monthly revenue that a customer generated over a one year period (April 2007 – March 2008). The operationalization of all variables appears in Table 3.2.

Table 3.2: Operationalization of variables

Variable	*Operationalization*
Nadopters_t	Number of adopters in the ego network of the focal customer in month t
Homophily_t	Average homophily among the adopters in the ego network of the focal customer in month t
Tie strength_t	Average tie strength among the adopters in the ego network of the focal customer in month t
$\text{Direct marketing}_t$	Stock variable of direct marketing received in the last four months
Age	Age (in years)
Usage	Natural logarithm of the average monthly revenue (euros) over a one-year period
Income	1 = below standard income; 2 = standard income; 3 = 1.5 standard income; 4 = 2 times standard income; 5 (ref. cat.) = more than 2 times standard income
Gender	Gender dummy (0 [ref. cat.] = female; 1 = male)
$\text{NadoptersXmarketing}_t$	Interaction between Nadopters and direct marketing
$\text{NadoptersXstrength}_t$	Interaction between Nadopters and tie strength
var FPj	Variable used to estimate the parameter of fractional polynomial j of variable 'var'

3.3.2 Data on social networks

We use CDR of a mobile telecom operator to create networks. In CDR data, all phone calls and text messages are recorded. We assume that a person's mobile phone network is a good proxy for his or her social network (Eagle, Pentland, and Lazer 2009; Haythornthwaite 2005). Prior research has used mobile call graphs to analyze network effects to model retention (Nitzan and Libai 2011) and adoption (Hill, Provost, and Volinsky 2006). The calling data can easily be complemented with customer and relationship data because they come from a telecom operator that also typically has access to a corresponding customer database. Another advantage of calling data is that actual communications between consumers are observed, and thus the strength of the relationship can be inferred from the volume of communication.

For this study, we collected CDR data during March, April, and May of 2008. We only included phone calls to and from mobile phones within the Netherlands. We used the CDR data to construct 15,708 ego networks, one for each customer in the sample. We define a tie as a reciprocal contact between two people, by text messages and phone calls. We measure the strength of a tie as the ratio of the volume of communication over the tie to the total communication volume of the focal customer within the observation period of three months (Nitzan and Libai 2011; Onnela et al. 2007). The variable we use to infer the effect of social influence in month t is the number of contacts that adopted in month t-1 ($Nadopters_{t-1}$). Prior research has also used this measure (e.g., Nitzan and Libai 2011; Onnela et al. 2007), which tends to be more informative than the dichotomous network neighbor variable that Hill, Provost, and Volinsky (2006) use. We assume that the mobile phone network is a good proxy for a customer's real social network and that it is constant over time (Haythornthwaite 2005).

3.3.3 Identification of social influence

An important aspect of modeling the effects of social influence is ensuring that the effect can indeed be attributed to social interaction (Hartmann et al. 2008; Manski 2000). Van den Bulte and Lilien 2001 (2001) empirically illustrate this identification problem and find that the effects of social contagion disappear when marketing activities are taken into account. This is an example of correlated effects (Manski 2000): Two people show similar behavior not because one influences the other but because both were influenced by a marketing campaign. To minimize the influence of such correlated effects we included marketing efforts and a function of time in our model. Another issue is that it is hard to assess whether the behavior of an individual in a group is caused by the group's behavior or whether the group's behavior is caused by the behavior of the individual (Manski 2000). To avoid this so-called reflection problem, we included lagged independent variables; that is, the number of adoptions by contacts at time t – 1 possibly influences adoption of the focal customer at time t.

Homophily, or "the principle that a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, and Cook 2001, p. 416), is another phenomenon that complicates the analysis of social interactions. With homophily, the "treatment" in the social network analysis of adoption (i.e., having contacts who adopted) is not fully random. That is, people with contacts who adopted are more likely to adopt because they are similar to their contacts, independent of social influence. We measure homophily on the basis of the similarity between consumers on sociodemographic variables. Specifically, we use the following measure: Given that we have four variables (age, gender, education level, and income) related to homophily, similarity on each variable adds .25 to the homophily score (Brown and Reingen 1987; Nitzan and Libai 2011). Age is considered to be similar if the difference is smaller than or equal to five years.

3.4 MODEL SPECIFICATION AND ESTIMATION

We use a fractional polynomial hazard model to analyze the time of adoption (Royston and Altman 1994). The model is based on the standard hazard model that is typically used to model time-to-event data (Franses and Paap 2001; for applications in marketing see Landsman and Givon 2010; Steenkamp and Gielens 2003; Van den Bulte 2000). The hazard is the probability that the event of interest will take place in the next period given that it did not yet occur. We use the complementary log-log formulation of the hazard because the timing of adoption is a continuous process that we analyze on a monthly interval basis (Van den Bulte and Lilien 2003). We include a function of time to capture factors that affect all customers, such as mass-media advertising by the firm and adoptions by the unrelated others in the market.

3.4.1 Accounting for time-varying parameters

To incorporate time-varying parameters for social influence and direct marketing, we use a fractional polynomial approach (Berger, Schäfer, and Ulm 2003; Royston and Altman 1994). The fractional polynomial approach helps incorporate rather complex shapes of time-varying parameters. We use the procedure that Berger, Schäfer, and Ulm (2003) suggest to determine the optimal shape of the fractional polynomial. We define the time-varying parameter of variable X as $\beta_{X,t} = \beta_X + \sum_{j=1}^{m} (\beta_{XFPj} \times t^{(p_j)})$. We use a maximal degree of m = 2 and the set of powers P = {–2, –1, –.5, 0, .5, 1, 2, 3}, and for $p_1 = p_2 = p$, we define $\beta_{X,t} = \beta_X + \beta_{X,FP1} \times t^p + \beta_{X,FP2} \times t^p \times \ln(t)$ (Berger, Schäfer, and Ulm 2003). We include time-varying parameters for social influence and direct marketing. We use the results of the base model (without the fractional polynomials) to determine the parameter for which the polynomial structure is fitted first. We begin with the variable with the lowest corresponding *p*-value in the base model. We determine the optimal values for the degree m and the powers p_j by minimizing the *p*-values of the likelihood ratio tests in which we compare the model with and without the fractional polynomial. In the base model, we define the hazard of adoption of customer i in month t as

$$(3.1)\quad h_{it} = 1 - \exp\left[-\exp\left[\begin{array}{l}\beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 \text{Nadopters}_{i,t-1} + \beta_4 \text{homophily}_{i,t-1} + \beta_5 \text{strength}_{i,t-1} + \\ \beta_6 \text{marketing}_{it} + \beta_7 \text{age}_i + \beta_8 \text{usage}_i + \beta_9 \text{income1}_i + \beta_{10} \text{income2}_i + \\ \beta_{11} \text{income3}_i + \beta_{12} \text{income4}_i + \beta_{13} \text{gender}_i\end{array}\right]\right]$$

Table 3.2 provides an explanation of the variable labels.

3.5 RESULTS

3.5.1 Model choice

We first estimated five versions of the model before determining the fractional polynomials for the social influence (Nadopters) and direct marketing parameters. Model 1 is the full model with only main effects including a function of time, the network variables (Nadopters, tie strength, homophily), direct marketing, and the control variables. We used Models 2–5 to investigate whether the various blocks of the model improved the model fit, and we used the Akaike information criterion (AIC) to compare the five models. Table 3.3 shows the estimation results. Model 1 has the lowest AIC (43412), and therefore we continued the analysis with Model 1 as our base model.

3.5.2 Hypothesis testing

In Model 1, the *p*-value corresponding to the effect of direct marketing is the lowest, and so we begin by determining the polynomial for the marketing effect. We estimated models for all possible combinations of powers with degrees 1 and 2. None of the likelihood ratio tests had a *p*-value lower than .05, and thus adding fractional polynomials for the direct marketing effect did not significantly improve the model. We conclude that the effect of direct marketing is positive and significant (β_6 = 1.094, $p < .001$) and constant from the product introduction onward. These findings regarding the direct marketing effect support H_{2a} and H_{2b}.

Table 3.3: Parameter estimates of Models 1–5

	Model 1		**Model 2** *Model 1 with interactions*		**Model 3** *Model 1 without time trends*		**Model 4** *Model 1 without network variables*		**Model 5** *Model 4 without marketing*	
	Estimate	***p***	***Estimate***	***p***	***Estimate***	***p***	***Estimate***	***p***	***Estimate***	***p***
Constant	−7.283	<0.001	−7.282	<0.001	−4.630	<0.001	−7.275	<0.001	−7.249	<0.001
t	0.223	<0.001	0.223	<0.001			0.223	<0.001	0.231	<0.001
t2	−0.003	<0.001	−0.003	<0.001			−0.003	<0.001	−0.004	<0.001
Nadopters	0.175	0.040	0.165	0.070	0.365	<0.001				
Homophily	0.252	0.145	0.261	0.137	0.448	0.008				
Tie strength	1.101	0.003	0.354	0.883	1.217	0.001				
Direct marketing	1.096	<0.001	1.094	<0.001	1.037	<0.001	1.096	<0.001		
NadoptersXmarketing			0.018	0.919						
NadoptersXstrength			0.745	0.752						
Age	−0.005	<0.001	−0.005	<0.001	−0.004	<0.001	−0.005	<0.001	−0.005	<0.001
Usage	0.282	<0.001	0.282	<0.001	0.247	<0.001	0.286	<0.001	0.340	<0.001
Income1	−0.214	<0.001	−0.214	<0.001	−0.195	<0.001	−0.224	<0.001	−0.212	<0.001
Income2	−0.256	<0.001	−0.256	<0.001	−0.237	<0.001	−0.263	<0.001	−0.253	<0.001
Income3	−0.181	<0.001	−0.181	<0.001	−0.168	<0.001	−0.186	<0.001	−0.186	<0.001
Income4	−0.105	0.022	−0.105	0.022	−0.090	0.050	−0.108	0.018	−0.100	0.030
Gender (male = 1)	0.070	0.024	0.070	0.024	0.063	0.042	0.072	0.021	0.074	0.018
AIC	43412		43416		45929		43453		43772	

Next, we determined the optimal fractional polynomial for the parameter of the Nadopters variable. The optimal model, based on the likelihood ratio test, had degree 2 and powers (3, 3). This is the combination of the highest possible degree and powers, and thus this could be a boundary solution. To investigate whether higher powers would improve the fit, we estimated additional models with powers higher than 3. The optimal model (Model 6) was indeed the model with degree 2 and powers (3, 3). Table 3.4 shows the parameter estimates and the corresponding *p*-values of this model. Figure 3.3 shows the time-varying effect and the approximate 95% confidence bounds of the Nadopters variable. The effect is .75 in the first month, which then slowly declines over time. From month 17 onward, the zero is included in the confidence interval, and thus the effect is no longer significantly different from zero. Our findings regarding the dynamics of the social influence effect support H_{1a} and H_{1b}.

Table 3.4: Estimation results of Model 6: The model with a time-varying parameter for social influence

	Estimate	***p***
Constant	–9.496	<0.001
t	0.228	<0.001
t^2	–0.004	<0.001
Nadopters	0.752	<0.001
Nadopters FP1	–0.001	0.004
Nadopters FP2	0.0002	0.005
Homophily	0.275	0.111
Tie strength	1.125	0.003
Direct marketing	1.094	<0.001
Age	–0.005	<0.001
Usage	0.282	<0.001
Income1	–0.214	<0.001
Income2	–0.256	<0.001
Income3	–0.181	<0.001
Income4	–0.105	0.023
Gender (male = 1)	0.069	0.025
AIC	43406	

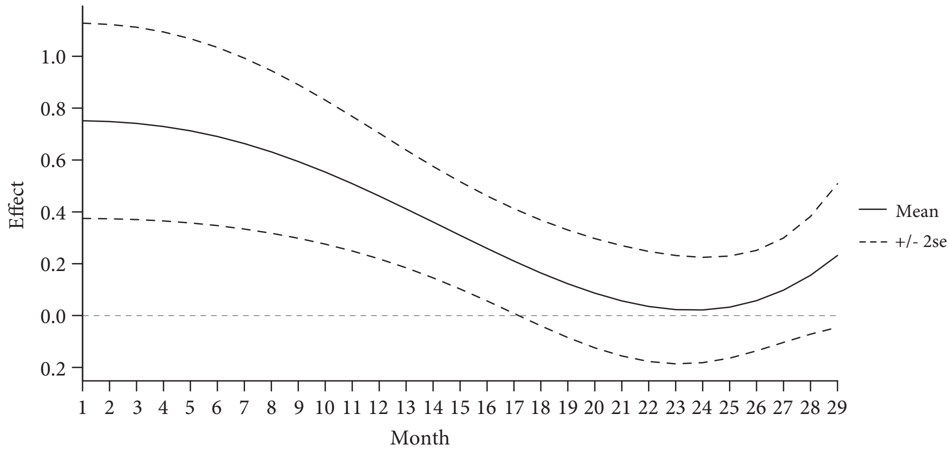

Figure 3.3: Time-varying effect of social influence

We used a z-test to compare the parameters of social influence and direct marketing in each period, where $z = (\beta_{3t} - \beta_6) / \sqrt{s.e.(\beta_{3t})^2 + s.e.(\beta_6)^2 - 2Cov(\beta_{3t}, \beta_6)}$ and $\beta_{3t} = \beta_3 + \beta_{3,FP1} \times t^3 + \beta_{3,FP2} \times t^3 \times \ln(t)$. We find that the parameters of social influence and direct marketing are not significantly different in the first four months ($p > .05$) and that the parameter of direct marketing is significantly larger from the fifth month onward. From these findings, we find no support for H_3.

Contrary to our expectations, the effect of homophily is not significant in the final model ($\beta_4 = .275$, $p = .111$). For the effect of tie strength, we find the expected positive effect ($\beta_5 = 1.125$, $p = .003$). In line with prior research, we find significant effects of sociodemographics and service usage. Age negatively affects adoption ($p < .01$), and men are more likely to adopt ($p < .05$). Income is also positively related to adoption; higher-income groups (two times the standard income and higher) are more likely to adopt than lower-income groups ($p < .01$). Finally, we find that customers with high service usage levels are more inclined to adopt ($p < .01$). From the findings that the interaction effect between social influence and direct marketing is not significant (.018, $p = .919$; see Model 2 in Table 3.3) and that the model without the interaction outperforms the model with the interaction, we find no support for H_4.

3.6 ROBUSTNESS CHECKS

We performed several robustness checks to determine whether the findings also held under alternative model specifications, which would increase our confidence in the results. The issues we investigated were unobserved heterogeneity and differences in susceptibility to social influence. We discuss the reasons for the checks and the results next.

3.6.1 Unobserved heterogeneity

Potential unobserved heterogeneity, or frailty, is a well-known issue in duration models (Therneau and Grambsch 2000). A random intercept, the frailty term, is included in the model to account for omitted variables and the likely early adoption of those who are most frail (intrinsically most likely to adopt). Early adoption by the most frail reduces the average adoption likelihood in the remaining part of the sample. We included a Gaussian frailty term ($u_{0j} \sim N(0, \Omega_u)$) in the model. The results of this model show that the frailty term is marginally significant (Ω_u = .078, SE = .04) and that no substantial changes occur in the remaining part of the model.

3.6.2 Susceptibility to social influence

We tested whether customers differ in their susceptibility to social influence because prior research in economics, consumer research, and psychology has suggested that gender and age moderate the effect of social influence. For gender, studies have found that women are more susceptible to social influence than men (Argys and Rees 2008; Eagly and Carli 1981; Venkatesh and Morris 2000). For age, psychological adult development theories posit that older people rely more on existing knowledge and have more stable beliefs than young people and thus are less susceptible to social influence (Hess 1994; Pasupathi 1999; Sears 1986). We checked this by including interactions between the Nadopters variable and the gender and age variables in the model. The moderation effects were not significantly different from zero and did not improve the overall fit of the model. We thus conclude that these differences in susceptibility do not need to be incorporated in the model.

3.7 DISCUSSION

During the past decade, marketers have shown a renewed interest in the effects of social influence. Social network data are becoming easier to obtain, and firms are searching for ways to compensate for the decreasing effectiveness of traditional instruments, such as direct marketing and mass-media advertising. Thus, an increasing number of studies have analyzed social networks and their effects on customer behavior (Libai et al. 2010; Van den Bulte and Wuyts 2007). In this study, we go beyond merely showing that social influence occurs and investigate factors that affect social influence. This study contributes to the literature stream by examining the time-varying effects of social influence and marketing and by assessing the interaction between social influence and direct marketing. Importantly, this study is among the few studies to include social influence effects in models in customer management, which have typically considered behavior in customer relationships while ignoring network effects (Libai et al. 2010; Van Doorn et al. 2010). The social influence effect in month t is defined as the effect of an adoption in month t-1 in the ego network of the customer. In Table 3.5, we summarize the main findings of this study. We discuss these and their implications for marketing theory and practice subsequently.

Table 3.5: Summary of the hypothesis testing results

Hypothesis		***Accepted?***
H_{1a}	The effect of social influence on adoption is positive.	✓
H_{1b}	The effect of social influence on adoption decreases from the product introduction onward.	✓
H_{2a}	The effect of direct marketing on adoption is positive.	✓
H_{2b}	The effect of direct marketing on adoption is constant from the product introduction onward.	✓
H_3	The effect of social influence on adoption is stronger than the effect of direct marketing in the early stage of the product life cycle.	×
H_4	Social influence increases the effect of direct marketing on adoption.	×

The decrease of the social influence effect from the product introduction onward is in line with recent work on adoption at the aggregate level (Bell and Song 2007; Choi, Hui, and Bell 2010) and the diffusion literature (Easingwood, Mahajan, and Muller 1983; Van den Bulte and Lilien 1997; Van den Bulte and Stremersch 2004). An explanation for this decrease pertains to information substitution dynamics; a pool of common knowledge develops over time, which leads to a decrease in the relative importance of new information obtained from other sources (Choi, Hui, and Bell 2010). Our results clearly emphasize the need to account for dynamics when studying social influence effects. That is, accounting for dynamics is important not only when studying advertising or promotion effects (e.g., Ataman, Van

Heerde, and Mela 2010; Leeflang et al. 2009; Osinga, Leeflang, and Wieringa 2010) but also when modeling the effect of social influence on behavior in customer relationships. These dynamics are less relevant for the effect of direct marketing. In line with our expectations, we found a constant effect of direct marketing from the product introduction onward. We argue that this is due to the persuasive objective of direct marketing. Because we only observe the presence of a direct marketing action and not the specifications, we can conclude that the effect of a direct marketing action is constant, but the way the effect is achieved might change from the product introduction onward.

Our individual-level approach enabled us to compare the effects of direct marketing with the social influence effect. We found that the effect of direct marketing is equal to the social influence effect in the first four months but becomes stronger from the fifth month onward. These findings are contrary to common knowledge that interpersonal influence is more important than firm-initiated influence. However, we find that the effect of an adoption in the ego network of the customer is less than the effect of one direct marketing action. When we account for the possibility of multiple adoptions in an ego network, the dominance of the effect of direct marketing does not hold in general. To compare the effectiveness of social influence and direct marketing in terms of return on investment (for resource allocation purposes), additional simulations and experiments are required. In addition, we found no evidence for synergy between social influence and direct marketing. The interaction effect between the two was not significant. We could argue that when customers are influenced by other consumers, they are more affected by marketing efforts. This notion might have important consequences for firms. If firms can develop effective strategies to create strong social influence effects (i.e., through viral marketing), they might need less traditional (individual) marketing efforts to obtain the same effect. This study does not provide evidence for such effects. Instead, the results suggest that firms still need direct marketing to influence behavior in customer relationships beyond the (weaker) effect of social influence. Additional research that simultaneously investigates social influence and marketing effects would be worthwhile.

3.8 MANAGEMENT IMPLICATIONS

Traditional marketing instruments have become less effective over the years. Prior research has shown that consumers are inclined to avoid these instruments (Hann et al. 2008). This avoidance is facilitated by technological devices, such as digital video recorders, that allow consumers to easily skip commercial breaks in television programs. Thus, marketers need to discover new ways to reach the consumer. The increasing availability of network data, combined with substantial information technology improvements that enable storing and analyzing of these data, has triggered marketers' interest in exploiting their customers' social networks. Social network (or viral) marketing has become a popular instrument and is often presented as the alternative for traditional direct marketing (De Bruyn and Lilien 2008; Hinz et al. 2011; Schmitt, Skiera, and Van den Bulte 2011). The results of this study provide insights to marketers that want to use social campaigns. We discuss the timing of such campaigns and whether social network marketing is indeed a substitute for direct marketing, which would have serious consequences for budget allocation.

With respect to timing of social campaigns, we recommend that marketers use them in the first months after the product introduction. We find that the effect of social influence decreases from the product introduction onward. Thus, in the first few months, the information that consumers spread to others is most valuable, and firms can benefit from this "free flow" of information. As time progresses, consumers might still discuss the product, but we do not observe a significant effect of social influence on adoption.

Given the positive effects of social influence, does the effect of direct marketing change in the current networked society? It could be that direct marketing becomes less effective in the presence of social influence, because consumers might hear about a product from their network and become annoyed when receiving additional attempts by the firm to persuade them. However, we could also argue that direct marketing might be more effective in the presence of social influence, because consumers are already aware of and informed about a product before the marketing action, which increases the likelihood to respond. In this study, we find no supporting evidence for these two scenarios. Rather, we find that direct marketing has a positive and constant effect on adoption and that this effect is not affected by social influence. In other words, the effects of direct marketing and social influence are independent, which suggests that marketers do not gain or lose from using the instruments simultaneously. Social network marketing is simply an addition to the marketing toolkit, not a replacement for currently used instruments.

3.9 RESEARCH LIMITATIONS

This study has several limitations; some are more general nature, whereas others specifically apply to the social influence focus of this study. In turn, these limitations could provide avenues for further research. First, we find that the social influence effect is decreasing from the product introduction onward, but due to our modeling approach we are not able to show what causes the decrease. We provide some possible explanations, but it is likely that many factors affect the social influence effect (Easingwood, Mahajan, and Muller 1983). Investigating these causes would be an interesting area for future research. Second, we studied a single application that pertained only to the adoption of a new smartphone. Although the individual communication-based network data we use are unique, they are from a single firm. Third, we examined social influence on adoption only, whereas prior research has shown that churn, for example, is also a social process (Nitzan and Libai 2011). However, the goal of this study was to enrich understanding of social influence on adoption, and thus we leave comparison of the different processes to further research. Fourth, we included only direct marketing and ignored mass-marketing data (e.g., at the brand level) because we did not have access to that data. We partially correct for this by including a function of time in our hazard model. Fifth, we did not have access to the content of the communication on which the networks are based. We assume that connected people influence one another similarly, but we did not investigate whether they actually discuss mobile phones with one another. Further research might include a substantive analysis of the conversations among customers in a network using data from new social media (e.g., Twitter, Facebook). Finally, there are several modeling issues that we aim to address in future work. The marketing variable in our model may be endogenous; using an instrumental variable approach would allow us to check whether this is indeed problematic in the current study. Another issue that our results might suffer from is a selection bias due to the fact that we only include those customers in the sample that remained a customer until the end of the observation period. Despite these limitations, we hope that this study stimulates further research in this area.

Chapter 4

An Empirical Investigation of the Determinants of Social Influence in Customer Ego Networks** ††

4.1 INTRODUCTION

Marketers have become very interested in social influence on the behavior in customer relationships and have high expectations regarding the use of it as a marketing tool. This is illustrated by the large investments of firms in social network marketing (Williamson 2010) and the high valuations for online social networks (Baldwin 2011; Graig and Sorkin 2011). A large body of research supports the notion that the behavior of customers is affected by the behavior of related others, thus we know that social influence occurs (e.g. Bell and Song 2007; Katona, Zubcsek, and Sarvary 2011; Nitzan and Libai 2011; Van den Bulte and Joshi 2007). What remains unclear, though, is why some customers are more influential than others (Godes 2011; Iyengar, Van den Bulte, and Choi 2011; Van den Bulte 2010). Understanding what the determinants of influence of initiators on (potential) followers are, is crucial for setting up successful social network marketing campaigns (e.g., viral and referral campaigns).

Research on the determinants of social influence has been done across multiple disciplines and different perspectives on what drives social influence have evolved. We classify these in three groups: network characteristics, customer relationship characteristics,

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** This chapter is based on Risselada, Hans, Peter C. Verhoef, Tammo H.A. Bijmolt (2011), "An Empirical Investigation of the Determinants of Social Influence in Customer Ego Networks," working paper, University of Groningen.

†† We acknowledge the financial support from the Marketing Science Institute (Grant No. #4-1706).

and personal characteristics. Despite the valuable insights that these different perspectives have given us, we identify three unresolved issues, 1) Is social influence driven mainly by network characteristics, customer relationship characteristics, or personal characteristics, 2) How does the impact of these determinants differ across products and behaviors?, and on a more detailed level, 3) What type of customers, in terms of centrality and usage, have the strongest influence as initiators on followers?

In this study we empirically investigate the determinants of social influence in the mobile telecom industry. We use a unique dataset consisting of network data, customer relationship data, and survey data that allows us to combine the three prevalent perspectives in the extant literature. We study two behaviors (adoption and churn) and we study adoption of two different products (high and low risk), using a separate model for all three dependent variables. We infer social networks from mobile phone communication patterns and determine social influence using observed behavior instead of self-reported influence measures.

The main contribution of this study is that we assess factors pertaining to the three prevalent perspectives on what drives social influence and investigate how the determinants of social influence differ across products and behaviors. Overall we find most evidence in support of the network characteristics as the drivers of social influence. We show that in contrast to a large body of word of mouth research, personal characteristics have only limited impact on actual social influence; network characteristics are more important. Furthermore, we find substantial differences between the impact of the determinants over the different products and behaviors. Finally, we contribute to the discussion on the effects of degree centrality and service usage on social influence. More specifically, we find that only in case of high risk product adoption, social influence is largest for initiators who are 1) light users, 2) customers with a high degree centrality, and 3) committed customers.

The remainder of this chapter is structured as follows. First, we present a concise overview of the literature on the different perspectives on what drives social influence and we describe the conceptual framework of our study. Second, we describe our data and elaborate on the econometric model, followed by an overview of the results. Then, we discuss the main findings and offer management implications. We conclude with the limitations of the current study and provide suggestions for future research.

4.2 CONCEPTUAL FRAMEWORK

In this study we examine social influence from a customer who has already shown a particular behavior (initiator) on the behavior of another customer (potential follower) in the ego network of the initiator. Different perspectives on what determines this kind of social influence have evolved. We classify the determinants in three groups: network characteristics, customer relationship characteristics, and personal characteristics. The conceptual model of this study (Figure 4.1) contains these determinants on social influence (the three boxes on the left side of the model). Each box represents variables that potentially affect the social influence exerted by the initiator over the others in his/her ego network. As shown in the right upper corner in Figure 4.1, we control for a number of characteristics of the initiator and the follower to disentangle the social influence from the intrinsic likelihood to show the behavior.

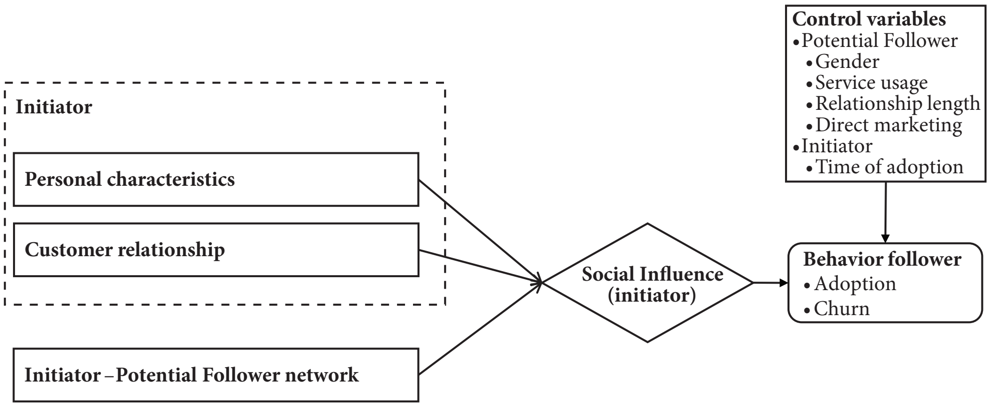


Figure 4.1: Conceptual model

Research on the determinants of social influence is done in various disciplines, such as marketing, sociology, social psychology, and economics. Table 4.1 provides an overview of the key publications in leading marketing journals on each of the three perspectives. We focus on social influence in a social contagion and word of mouth context. In the following sections we provide a short overview of the literature and discuss the rationales behind the variables and the corresponding effects in the model.

Table 4.1: Literature on the three perspectives on social influence

Study	*Relevant finding(s)*
Network characteristics	
Aral, Muchnik, and Sundararajan 2009	– Previous methods overestimate peer influence by 300-700%. – Homophily explains >50% of the perceived behavioral contagion.
Goldenberg et al. 2010	– Neighborhood adoption positively affects social influence.
Hansen 1999	– Weak ties speed up projects when knowledge is not complex but slows them down when the knowledge to be transferred is highly complex.
Hinz et al. 2011	– Hubs are the best seeds for a referral campaign.
Katona, Zubcsek, and Sarvary 2011	– Degree centrality negatively affects social influence.
Leskovec, Adamic, and Huberman 2007	– Degree centrality negatively affects social influence.
Levin and Cross 2004	– Tie strength positively affects social influence. – Controlling for trust, the effect of weak ties was stronger.
Manchanda, Xie, and Youn 2008	– Contagion positively affects adoption.
Nair, Manchanda, and Bhatia 2011	– Prescription behavior is significantly influenced by opinion leaders.
Nitzan and Libai 2011	– Tie strength positively affects social influence. – Homophily positively affects social influence.
Trusov, Bodapati, and Bucklin 2010	– About one fifth of a user's friends actually influence his/her activity on the site.
Personal characteristics	
Berger, Cohen, and Zelditch Jr. 1972	– Status positively affects social influence.
Burnkrant and Cousineau 1975	– Informational influence was at work.
Dichter 1966	– Product-involvement, self-involvement, other-involvement, and message-involvement positively affect word of mouth.
Feick and Price 1987	– Market mavenism positively affects social influence.
Frenzen and Nakamoto 1993	– Subjects behaved toward weak ties as if there were a risk posed by the moral hazard. – Strong ties, by contrast, are highly robust to information characteristics.

Study	***Relevant finding(s)***
Godes and Mayzlin 2009	– Firm initiated word of mouth is less effective in the loyal customer segment.
Hennig-Thurau et al. 2004	– Economic incentives, concern for others, and extraversion/self-enhancement positively affect word of mouth.
Im, Mason, and Houston 2007	– Personal communication positively affects product adoption. – Innovativeness positively affects word of mouth.
Iyengar, Van den Bulte, and Valente 2011	– Usage positively affects social influence.
Katz and Lazarsfeld 1955	– Opinion leadership is based on: who one is, what one knows, whom one knows
Kratzer and Lettl 2009	– They find distinctive roles of lead users and opinion leaders.
Matzler, Pichler, and Hemetsberger 2007	– Extraversion positively affects word of mouth.
Mooradian and Swan 2006	– Extraversion (of cultures) positively affects word of mouth.
Myers and Robertson 1972	– Self-reported opinion leadership is positively related to knowledge about a topic, discussion about it, and the amount of interest in it.
Price and Feick 1984	– Interpersonal sources of information are more likely to be used than other types of sources. – Informational social influence is important.
Richins and Root-Shaffer 1988	– Opinion leadership positively affects word of mouth. – Situational involvement positively affects word of mouth.
Westbrook 1987	– Positive and negative affect are related to the extent of word of mouth transmission. – Satisfaction shows a weak negative effect on word of mouth once the affective influences have been partialled out.
Relationship marketing characteristics	
Bettencourt 1997	– Commitment positively affects word of mouth.
Brown et al. 2005	– Commitment positively affects word of mouth.
De Matos and Rossi 2008	– Commitment positively affects word of mouth. – Loyalty positively affects word of mouth. – Studies on word of mouth behavior show a weaker loyalty-wom link than studies on word of mouth intentions.

Study	*Relevant finding(s)*
Hennig-Thurau, Gwinner, and Gremler 2002	– Satisfaction and commitment positively affect word of mouth.
Palmatier et al. 2006	– Commitment positively affects word of mouth.
Reynolds and Beatty 1999	– Satisfaction and relationship length (retail/salesperson setting) positively affect word of mouth.
Swan and Oliver 1989	– Satisfaction and equity were both related to more positive word of mouth.
Verhoef, Franses, and Hoekstra 2002	– Commitment and satisfaction positively affect the number of referrals.
Wangenheim and Bayón 2007	– Satisfaction positively affects word of mouth both in a b2c and b2b setting.
Zeithaml, Berry, and Parasuraman 1996	– Commitment positively affects word of mouth both in a b2c and b2b setting.

4.2.1 Network characteristics

Studies that take a network perspective on social influence investigate whether and how the properties of a consumer's network affect the amount of social influence s/he exerts. The two structural network properties that have received most attention in the literature are tie strength and degree centrality. They are well-suited for our ego network analysis, because they do not require data of the entire network (Van den Bulte and Wuyts 2007).

The effect of tie strength on social influence is much-debated. Weak ties are considered to be important for the flow of information through a network because they typically bridge gaps between separate parts of the network (Granovetter 1973). However, others have shown that the flow of complex information and referrals requires stronger relationships (Frenzen and Nakamoto 1993; Hansen 1999; Reingen and Kernan 1986). In support of this, Nitzan and Libai (2011) have found a positive effect of tie strength on social influence in the case of churning on a mobile phone subscription. Levin and Cross (2004) argue that trust is the key moderating variable of the relationship between tie strength and the flow of information; controlling for trust they found that weak ties are most important for knowledge sharing in an organization because of the bridging function mentioned above. The amount of trust that is required in a relationship to exchange information about a particular type of behavior is likely to depend on the amount of risk associated with that behavior. Thus the effect of tie strength on social influence is likely to be product- and behavior-specific.

Degree centrality is the total number of others with whom a customer has a direct relationship in a network. Individuals with an extremely high degree centrality, the so-called hubs, accelerate the adoption process and positively affect the total market size of new products (Goldenberg et al. 2009; Goldenberg, Lowengart, and Shapira 2010). These positive relations are both found on the micro-level and the macro-level, though on the micro-level the results are more diverse. Goldenberg et al. (2008) find that the influence of hubs on adoption depends on the product and on the particular consumer that is looking for information. Trusov, Bodapati, and Bucklin (2010) show that on average only about a fifth of a consumer's contacts on a social network site actually influence his/her behavior, which implies that the effect of hubs on their networks might be limited. Katona, Zubcsek, and Sarvary (2011) and Nitzan and Libai (2011) indeed provide evidence for a negative effect of degree centrality. It takes a certain amount of effort to exert influence on another person and a larger number of contacts implies less effort per contact (Hinz et al. 2011; Leskovec, Adamic, and Huberman 2007).

The third variable that we consider as part of the network characteristics is homophily. Homophily is the phenomenon that people tend to associate with others like them (McPherson, Smith-Lovin, and Cook 2001). Similar people are likely to behave similarly (Van den Bulte and Wuyts 2007). We consider it a network property because it captures the similarity between two connected individuals and thus requires knowledge of the network. Aral, Muchnik, and Sundararajan (2009) show that ignoring homophily results in an average overestimation of social influence effects by 300-700%. They also show that homophily explains 50% of the behavior that is typically labeled as contagion. Nitzan and Libai (2011) include homophily in a social influence model for churning behavior and find that an increase of 1% in homophily with churners you are related to increases your hazard to churn with 1%. These findings illustrate that it is crucial to include homophily in social influence models.

4.2.2 Relationship marketing characteristics

In the relationship marketing literature social influence mainly received attention as word of mouth behavior or intentions in the form of (intended) recommendations, referrals, and the net promoter score (Palmatier et al. 2006; Reichheld 2003; Sirdeshmukh, Singh, and Sabol 2002). Researchers with this perspective frequently investigated characteristics of the customer-firm relationship as drivers of social influence. Commitment captures the current satisfaction of the customer as well as the intention to continue the relationship in the future (Morgan and Hunt 1994). Hence, it is a very informative characteristic of relationship quality (De Wulf, Odekerken-Schroder, and Iacobucci 2001; Kumar, Scheer, and Steenkamp 1995). Palmatier (2008) argues that relationship quality is similar to the tie strength between two exchange parties. However, to avoid confusion here we use the term tie strength for the relationship between the initiator and the follower and commitment for the relationship between the initiator and the firm. In the relationship marketing context, the positive relationship between commitment and word of mouth has been found for business-to-consumer relationships (Bettencourt 1997; Brown et al. 2005; De Matos and Rossi 2008; Dick and Basu 1994; Harrison-Walker 2001; Hennig-Thurau et al. 2004; Swan and Oliver 1989; Verhoef, Franses, and Hoekstra 2002) as well as for business-to-business relationships (Wangenheim and Bayón 2007; Zeithaml, Berry, and Parasuraman 1996). For example, Reynolds and Beatty (1999) show that customers that are committed to a salesperson are more likely to engage in word of mouth about the salesperson and the company. In summary, the literature suggests that customers exert more social influence about a firm's products and services if they are more committed to a firm.

Social influence through word of mouth does not necessarily lead to behavior by the related other, because word of mouth intentions do not necessarily translate into actual word of mouth behavior (De Matos and Rossi 2008) and word of mouth behavior does not necessarily translate into actual influence. This suggests a weakly positive or even absent relationship between commitment and social influence. The relationship can also be negative, that is customers that are not committed to a firm could have more impact on others. The rationale for this is as follows; if a person recommends a firm that s/he is not (very) committed to, then it must be really good. So despite the lower frequency of recommendations, the effect of a single recommendation could be higher, similar to the negative effect of higher degree centrality (Katona, Zubcsek, and Sarvary 2011; Nitzan and Libai 2011). Summarizing, the direction of the moderating effect of commitment on social influence is unclear a priori.

4.2.3 Personal characteristics

Personal characteristics are heavily researched in the areas of psychology and consumer behavior. We distinguish three groups of variables based on earlier research, namely product knowledgeability (e.g., self-reported opinion leadership, innovativeness, and perceived knowledge), personality traits (e.g., extraversion), and service usage. Study designs in this area are diverse in that associations among those variables have been studied and some variables have been used as independent as well as dependent variables. For example, opinion leadership has been used as a proxy for social influence (as a dependent variable) and as an independent variable to explain social influence (Coulter, Feick, and Price 2002; Richins and Root-Shaffer 1988). Personal characteristics that have been shown to affect social influence positively are: innovativeness (Im, Mason, and Houston 2007), involvement (Dichter 1966; Richins and Root-Shaffer 1988; Sundaram, Mitra, and Webster 1998; Westbrook 1987), perceived knowledge (Myers and Robertson 1972), extraversion (Hennig-Thurau et al. 2004; Matzler, Pichler, and Hemetsberger 2007; Mooradian and Swan 2006; Sundaram, Mitra, and Webster 1998), and status (Berger, Cohen, and Zelditch Jr. 1972).

Extraversion is a commonly researched personality trait in relation to social influence (Cuperman and Ickes 2009). It is defined as 'the degree to which an individual is outgoing, energetic, and experiences motivation' (Funder and Fast 2010, p. 679). Extravert consumers are more outgoing, that is more active in spreading the word about their actions, and are thus more likely to influence others around them (Hennig-Thurau et al. 2004; Matzler, Pichler, and Hemetsberger 2007; Mooradian and Swan 2006; Sundaram, Mitra, and Webster 1998). This rationale implies a positive effect of extraversion of the initiator on social influence. Cuperman and Ickes (2009) show that extraversion is not affecting the frequency and duration of conversations with others, but does affect the directness of the conversation. Furthermore, they show that extravert individuals are more confident speakers and convinced that the other person likes and accepts them. These mechanisms support the expected positive effect of extraversion on social influence.

Service usage is an indicator of the level of experience with the product and hence it is likely that related others infer status from high usage levels (Iyengar, Van den Bulte, and Valente 2011). Based on this rationale, one would expect heavy users to be more influential (Berger, Cohen, and Zelditch Jr. 1972). However, the empirical findings on the influence of heavy users are mixed so far (Van den Bulte 2010). In a pharmaceutical context, Iyengar, Van den Bulte, and Valente (2011) indeed find a positive effect of usage (i.e., prescription behavior) on social influence. Similarly, Coulter, Feick, and Price (2002) find a positive association between opinion leadership and usage (e.g., spending) in a retail setting. However, Godes and Mayzlin (2009) find that heavy users are less active in spreading word of mouth. They argue that this is because heavy users are typically connected to other heavy users and that these have already made up their mind on the adoption decision. So, they either already adopted the product or decide not to do so and will not do it after the incremental word of mouth. Yet, in the pharmaceutical industry it is common practice to use high usage levels to identify influential individuals in a market (Manchanda, Rossi, and Chintagunta 2004). Clearly, more insights are needed on the relationship between service usage and social influence.

Despite the useful insights that the literature on personal characteristics and social influence has provided, it remains unclear to what extent they hold for actual influence due to the reasons mentioned above.

4.2.4 Different behaviors and products

The role of social influence has been studied for a wide variety of products, ranging from complex, high-risk products to free add-ons on online social networks. Some findings might be driven by the characteristics of the product under study. In addition, the social influence might be different for various behaviors.

In this study, we analyze different products and behaviors in the mobile telecom industry. We analyze the adoption of a new value-added service that enables customers to make an online backup of their phone numbers (phonebook), the adoption of a smartphone, and the churning decision on the subscription. These products and behaviors differ on dimensions such as innovativeness, complexity, and associated risk and thus potentially in the impact of social influence (Chen, Wang, and Xie 2011; Hahn et al. 1994). A key element here is the different underlying mechanisms that drive social influence. Social influence can occur as a result of increased awareness or as a result of persuasion. The exchange of simple information is likely to be sufficient for increasing awareness of the product, whereas the transfer of potentially complex information is required for persuasion (Murray 1991; Van den Bulte 2010). Based on this we expect that for complex and high risk products and behaviors, 1) tie strength will have a greater effect on social influence, 2) the effect of degree centrality is smaller or even becomes negative, and 3) product knowledgeability has a greater effect.

4.2.5 Interactions with tie strength

The strength of a relationship indicates how intensively two customers interact and thus how often initiators have the opportunity to share their knowledge or enthusiasm about a product with their network. It may be that the effect of tie strength depends on the type of initiator (Levin and Cross 2004). Knowledgeable, extravert, or committed initiators may not need strong relationships to get their message across, which implies a negative interaction between these variables and tie strength. It could also be that such initiators fully use the opportunity and exert even more influence over stronger ties. The latter implies a positive interaction. We will empirically explore these interactions in our model.

4.2.6 Control variables

To assess the importance of the determinants of social influence we control for a number of factors that might affect the behavior of the potential follower. We control for the characteristics of the potential follower by including gender, service usage (follower), and direct marketing (e.g., Arts, Frambach, and Bijmolt 2011; Prins and Verhoef 2007). To control for the type of adopter we include the time of adoption of the initiator in the smartphone and phonebook adoption models.

4.3 DATA

In this study we empirically investigate the determinants of social influence on adoption and churn in the mobile telecom industry. We used three sources of data: call detail records (CDR), a customer database, and an online survey. We started the data collection with a set of respondents of an online survey on a representative sample of the customer base of a large Dutch telecom operator in December 2010. We identified those respondents that were the first in their ego network to adopt a smartphone, to adopt a new value-added service, or to churn (the initiators). We used the CDR data of May-June 2010 to create ego networks for the initiators that adopted a smartphone ($n_{initiators}$=1692, $n_{potentialfollowers}$=7576), a new value-added service ($n_{initiators}$=706, $n_{potentialfollowers}$=7189), or churned from the subscription ($n_{initiators}$=355, $n_{potentialfollowers}$=1976). The adoption data was collected in the period January 2009 – February 2011 and the churn data in the period January – July 2011, all on a monthly basis. Because we study social influence that results from communication between two individuals, the choice to analyze the behavior within the ego network of an initiator is a natural one; indirect influence via others is no longer completely attributable to the original source. We use definitions for a tie and its strength from prior work in this area (Nitzan and Libai 2011; Onnela et al. 2007). The presence of a tie is based on reciprocal contact between two individuals, that is customer A contacted customer B and B contacted A, both at least once. We measure tie strength by communication volume, which is the number of calling minutes plus the number of text messages between the two. The degree centrality of the initiator is defined as the total number of direct relationships, which means the size of the ego network of the initiator. We measure homophily based on age, gender, education level, and income, where similarity on each of these variables adds 0.25 to the homophily score (Brown and Reingen 1987; Nitzan and Libai 2011). Age is considered to be similar if the difference is smaller than or equal to five years. The variable usage refers to the usage intensity of mobile telecom services and is measured as the average monthly revenue of a customer.

To enrich the data with relationship and personal characteristics we used the customer database of the telecom operator and the data from the online survey among the initiators. The telecom industry is very well-suited for social influence research since network data can be obtained and linked to behavioral data (e.g., Nitzan and Libai 2011).

4.3.1 Survey

We conducted an online survey in December 2010 to collect data on the personal and customer relationship characteristics of the initiators. We used items from standard scales in the literature to measure opinion leadership, extraversion, involvement, innovativeness, and perceived knowledge. We worked closely together with the firm to be able to include our questions in a larger customer survey. We adapted some of the scales to reduce the length of the survey and thereby increase the expected response rate. Table 4.2 presents an overview of the scales and items that we used and the papers in which they have been developed or used previously.

Table 4.2: Items used in the survey and the results of the principal component analysis

Factor	*Construct*	*Items*	*Adaptations from …*
Factor 1 Opinion leadership	Innovativeness	1. In general, I am the first in my circle of friends to buy a new mobile phone when it appears *(innov1)* 2. If I heard that a new a mobile phone was available, I would be interested enough to buy it *(innov2)* 3. I like to buy a new mobile phone before other people do *(innov3)*	Goldsmith and Hofacker 1991 Steenkamp and Gielens 2003
	Opinion leadership	4. When they choose a mobile phone, other people turn to me for advice *(opil1)* 5. I often persuade others to buy the mobile phones that I like *(opil2)*	Flynn, Goldsmith, and Eastman 1994 Kratzer and Lettl 2009
	Perceived knowledge	6. I belong to the 25% of the population that knows the most about mobile products/services *(perck1)* 7. I consider myself to be an educated consumer regarding mobile telephony *(perck2)*	Pritchard, Havitz, and Howard 1999 Heitmann, Lehmann, and Herrmann 2007 Flynn and Goldsmith 1999
Factor 2 Extraversion	Extraversion	8. I like to express my joy about good buys *(extrav1)* 9. I feel good when I can tell others about my buying successes *(extrav2)* 10. I like to tell others about a great experience *(extrav3)*	Hennig-Thurau et al. 2004
Factor 3 Commitment	Commitment	11. I feel XYZ knows what I want *(commit1)* 12. I feel a strong sense of belonging to XYZ *(commit2)* 13. I feel a strong sense of attachment to XYZ *(commit3)*	Verhoef 2003
Factor 4 Involvement	Involvement	14. Generally, I am someone who finds it important what mobile products/services he or she buys *(involv1)* 15. Generally, I am someone who is interested in the kind of mobile products/services he or she buys *(involv2)*	De Wulf, Odekerken-Schroder, and Iacobucci 2001

NOTE: These results are based on the smartphone adoption sample. The results for the other samples are very similar and available upon request.

We found high correlations between some of the items of different constructs (Table 4.3). This is not surprising given that prior research has shown that the product knowledgeability variables are all associated to each other (see the literature review). Therefore, we used a principal component analysis (PCA) to explore the factor structure. Tables 4.2 and 4.4 show the results of the PCA. The variance explained by four factors is larger than 70% and the eigenvalues of the factors are larger than 1 (Hair et al. 2006). Combined with the good interpretability of the resulting factors, we use the four factor solution. Several items pertaining to innovativeness, opinion leadership, and perceived knowledge have high loadings on factor 1. Opinion leadership is a broad concept and several authors have argued that innovativeness and perceived knowledge are part of the opinion leadership construct (Feick and Price 1987; Kratzer and Lettl 2009). Based on this, we call factor 1 the Opinion Leadership factor and it also captures the product knowledgeability construct of our theoretical framework. Factors 2, 3, and 4 correspond largely with the original scales of commitment, extraversion, and involvement respectively. We use the resulting factor scores as variables in our models. The operationalization of the other variables is shown in Table 4.5.

Table 4.3: Correlations between survey items

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
1. perck1															
2. perck2	.487														
3. extrav1	.246	.309													
4. extrav2	.222	.323	.746												
5. extrav3	.237	.292	.684	.793											
6. innov1	.530	.436	.256	.253	.255										
7. innov2	.449	.461	.301	.302	.309	.603									
8. innov3	.480	.386	.230	.245	.274	.726	.648								
9. involv1	.208	.278	.224	.205	.235	.253	.325	.279							
10. involv2	.279	.293	.208	.219	.212	.307	.375	.330	.614						
11. commit1	.067	.090	.140	.114	.143	.114	.155	.104	.084	.121					
12. commit2	.047	.105	.158	.155	.163	.074	.148	.090	.113	.131	.694				
13. commit3	.100	.132	.185	.162	.212	.139	.205	.161	.144	.162	.683	.786			
14. opil1	.720	.465	.300	.285	.276	.539	.435	.442	.200	.261	.102	.071	.115		
15. opil2	.482	.512	.342	.356	.365	.502	.468	.477	.248	.288	.126	.097	.181	.501	

NOTE: all correlations are significant ($p < .01$) except corr(perck1, commit2) with $p = .031$

Table 4.4: Rotated component matrix

	Component			
	1	*2*	*3*	*4*
innov1	**.811**	.064	.051	.144
perck1	**.804**	.084	-.001	.007
opil1	**.783**	.158	.026	-.018
innov3	**.754**	.059	.071	.216
innov2	**.691**	.142	.122	.289
opil2	**.674**	.274	.073	.101
perck2	**.629**	.223	.041	.158
extrav2	.192	**.906**	.063	.088
extrav3	.196	**.871**	.101	.102
extrav1	.205	**.854**	.087	.086
commit2	.023	.086	**.914**	.052
commit3	.103	.099	**.899**	.078
commit1	.075	.049	**.872**	.017
involv1	.166	.132	.049	**.868**
involv2	.251	.093	.074	**.839**

Table 4.5: Operationalization of the variables

Variable	*Operationalization*
Tie strength	Natural logarithm of the sum of the number of calling minutes and the number of text messages between the initiator and the follower
Homophily	Homophily between the initiator and the follower based on gender, age, education, and income
Degree centrality	Number of potential followers of the initiator
Direct marketing$_t$	Dummy variable that indicates whether the follower received direct marketing in the last month
Service usage	Natural logarithm of the average monthly revenue (euros) over a one-year period
Gender_male	Gender dummy (0 [ref. cat.] = female; 1 = male)
Relationship length	Length of the customer-firm relationship of the follower (in months)
t_initiator	Number of months between product introduction and the adoption moment of the initiator

4.4 METHOD

We model the timing of the behavior of a potential follower in the ego network of an initiator, and thereby assess the effects of network characteristics, quality of the relationship between the initiator and the firm, and personal characteristics of the initiator. The model is based on the hazard model, that is typically used to model time-to-event data (Franses and Paap 2001; for applications in marketing see Landsman and Givon 2010; Steenkamp and Gielens 2003; Van den Bulte 2000). The hazard is the probability that the event of interest will take place in the next period given that it did not occur yet. We use the complementary log-log formulation of the hazard because the timing of adoption and churn are continuous processes that we analyze on a monthly interval basis (Van den Bulte and Lilien 2003). The ego network of an initiator typically contains multiple potential followers; to account for this we use a multilevel version of the hazard model (Barber et al. 2000). Equation (4.1) shows the complementary log-log formulation of the hazard model and Equations (4.2) and (4.3) show the individual and ego network level of the linear part of the model. The hazard of potential follower i in the ego network of initiator j in month t (after the behavior of the initiator) for behavior b ($h_{b,ijt}$) is defined as:

$$(4.1)\quad h_{b,ijt} = 1 - \exp\left[-\exp\left[x^{(bij,t)}\beta_b\right]\right].$$

Here b indicates the type of behavior (sp = smartphone adoption, pb = phonebook adoption, c = churn). The model specifications are equal for the three behaviors so we dropped the subscript b from the equations below for notational convenience.

Individual level

$$(4.2)\quad x^{(ij,t)}\beta = \beta_{0jt} + \beta_{1j}\text{tie\_strenght}_i + \beta_{2j}\text{homophily}_i + \beta_{3j}\text{usage}_i, + \beta_{4j}\text{direct\_marketing}_{it} + \beta_{5j}\text{gender\_male}_i + \beta_{6j}\text{relationship\_length}_i + \upsilon_{ij}$$

Ego network level

$$(4.3)\quad \beta_{0jt} = \gamma_{00} + \gamma_{01}t + \gamma_{02}t^2 + \gamma_{03}\text{degree\_centrality}_j + \gamma_{04}\text{opinion\_leadership}_j + \gamma_{05}\text{commitment}_j + \gamma_{06}\text{extraversion}_j + \gamma_{07}\text{involvement}_j + \gamma_{09}\text{usage}_j + \gamma_{10}\,\text{t\_initiator}_j + \nu_{0j}$$

$$\text{and } \beta_{1j} = \gamma_{10}, \beta_{2j} = \gamma_{20}, \beta_{3j} = \gamma_{30}, \beta_{4j} = \gamma_{40}, \beta_{5j} = \gamma_{50}, \beta_{6j} = \gamma_{60}$$

We include two Gaussian frailty terms in the model ($\upsilon_{ij} \sim N(0, \Omega_{\upsilon})$, ($\nu_{0j} \sim N(0, \Omega_{\nu})$ to account for unobserved heterogeneity on the follower and the initiator level, respectively. We estimate the model in two steps. First, we estimate the models using a quasi-likelihood approach (IGLS). In the second step, we use the estimates from the first step as initial values for a Markov Chain Monte Carlo (MCMC) procedure. We use the default diffuse prior distributions in MLwiN 2.23, 500 iterations for the burn-in, and 30,000 iterations in total. We use the deviance information criterion (DIC) to assess model fit. To compare the impact of the three groups of determinants we use a leave-one-out approach, that is, we compare the DIC of the full model to the DICs of the model without one of the groups.

4.5 RESULTS

Table 4.6 presents an overview of the results of the models for the smartphone adoption, the phonebook adoption, and the churning decision. To reduce the skewness of the distributions we included log-transformed versions of relationship length, tie strength, and the service usage variables. In the subsections below we discuss the results for each group of determinants separately.

4.5.1 Network characteristics

We find a positive significant effect of tie strength in all three models ($\gamma_{sp,10}$=.038, Confindence Interval (CI) = (.010, .066); $\gamma_{pb,10}$=.173, CI=(.031, .316); $\gamma_{ch,10}$=.160, CI=(.031, .287)). This implies that social influence from an initiator to a follower is greater over stronger relationships between these customers. The results on the impact of degree centrality are mixed. We find a negative effect in the phonebook adoption model ($\gamma_{pb,03}$=-.094, CI=(-.171, -.021)), which implies that if the ego network of the initiator is larger, the social influence on a single potential follower is smaller. In the smartphone adoption model we find the opposite; the effect of degree centrality is positive ($\gamma_{sp,03}$=.022, CI=(.01, .035)). The effect of homophily is positive and significant in the smartphone adoption model ($\gamma_{sp,20}$=.271, CI=(.115, .428)) and the churn model ($\gamma_{ch,20}$=.844, CI=(.172, 1.523)). Hence, in these models we find support for increased social influence if the initiator and potential follower are more similar.

Table 4.6: Estimation results

	Smartphone	***Phonebook***	***Churn***
	Posterior mean [95% credible interval]	Posterior mean [95% credible interval]	Posterior mean [95% credible interval]
Intercept	**-9.257**	**-4.750**	**-5.223**
	[-9.916; -8.474]	[-9.142; -0.112]	[-9.426; -1.907]
t	**0.075**	-0.081	0.249
	[0.048; 0.102]	[-0.205; 0.045]	[-0.219; 0.774]
t^2	**-0.003**	0.005	-0.027
	[-0.004; -0.002]	[-0.001; 0.011]	[-0.113; 0.051]
Tie strength	**0.038**	**0.173**	**0.160**
	[0.01; 0.066]	[0.031; 0.316]	[0.031; 0.287]
Homophily	**0.271**	0.641	**0.844**
	[0.115; 0.428]	[-0.285; 1.563]	[0.172; 1.523]
Degree centrality	**0.022**	**-0.094**	-0.042
	[0.01; 0.035]	[-0.171; -0.021]	[-0.106; 0.023]
Opinion leadership	0.033	-0.061	0.091
	[-0.011; 0.077]	[-0.289; 0.165]	[-0.127; 0.308]
Involvement	**0.045**	0.115	0.009
	[0.002; 0.089]	[-0.115; 0.356]	[-0.212; 0.224]
Extraversion	0.004	0.108	0.156
	[-0.041; 0.048]	[-0.123; 0.355]	[-0.058; 0.379]
Service usage (initiator)	**-0.102**	-0.325	-0.017
	[-0.194; -0.04]	[-0.847; 0.112]	[-0.39; 0.371]
Commitment	**0.052**	-0.023	0.111
	[0.010; 0.095]	[-0.251; 0.211]	[-0.086; 0.307]
Gender (1=Male)	**-0.111**	0.171	0.061
	[-0.199; -0.023]	[-0.25; 0.595]	[-0.314; 0.433]
Relationship length	**0.525**	**-0.247**	-0.031
	[0.469; 0.58]	[-0.487; -0.009]	[-0.246; 0.194]
Service usage (follower)	**0.452**	**0.282**	0.069
	[0.399; 0.496]	[0.014; 0.532]	[-0.214; 0.352]
Direct marketing	**0.667**	**1.775**	
	[0.457; 0.874]	[0.801; 2.62]	
Time of adoption (initiator)	**0.014**	-0.002	
	[0.004; 0.024]	[-0.056; 0.049]	
Tie strength X Extraversion	**-0.039**		

	Smartphone	*Phonebook*	*Churn*
	Posterior mean [95% credible interval]	Posterior mean [95% credible interval]	Posterior mean [95% credible interval]
	[-0.068; -0.009]		
Tie strength X Opinion leadership	**0.034**		**0.144**
	[0.005; 0.062]		[0.020; 0.268]
Tie strength X Commitment		**0.188**	
		[0.058; 0.318]	
Ω_{ν}	**0.007**	**0.635**	**0.494**
	[0.0004; 0.046]	[0.008; 1.844]	[0.041; 1.409]
Ω_{υ}	**0.001**	**0.002**	**0.100**
	[0.0003; 0.005]	[0.0003; 0.005]	[0.002; 0.295]

NOTE: Bold numbers indicate significant effects

4.5.2 Relationship marketing characteristics

The role of commitment as a determinant of social influence is limited according to our results, because it is not significant in two of the three models. Commitment has a positive significant effect on smartphone adoption only ($\gamma_{sp,05}$=.052, CI=(.010, .095)). Customers that have a stronger intention to maintain their relationship with the firm are more inclined to spread the word about adoption of a smartphone but do not influence others more in cases of phonebook adoption or churn.

4.5.3 Personal characteristics

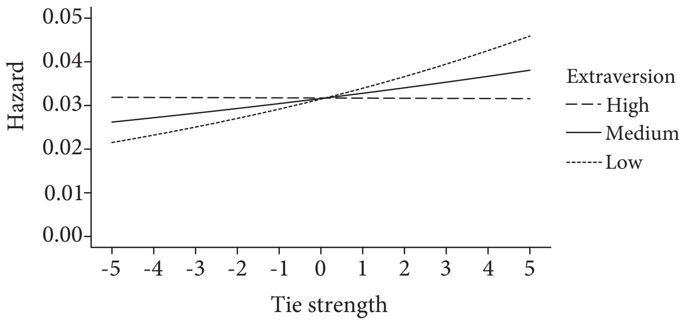
In line with prior research on the effect of involvement on social influence we find a positive and significant effect in the smartphone adoption setting ($\gamma_{sp,07}$=.045, CI=(.002, .089)). However, the effects of opinion leadership and extraversion are not significant in any of the models. So, although opinion leaders and extravert customers state that they like to share their experiences and purchases, they do not influence the behavior of others more than other initiators do. We find a negative effect of service usage of the initiator on smartphone adoption ($\gamma_{sp,09}$=-.102, CI=(-.194, -.04)). Here, initiators that are heavy users of the service exert less influence on the others in their ego network. The effect of service usage is also negative in the phonebook adoption and churn model, but does not reach significance there.

4.5.4 Interactions with tie strength

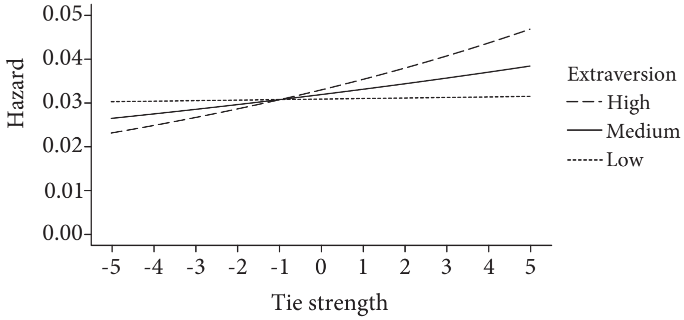
We included the interactions with opinion leadership, involvement, extraversion, and commitment simultaneously and kept those that were significant in the final models. We find a positive interaction between opinion leadership and tie strength for the smartphone adoption ($\gamma_{sp,tsXopil}$=.034, CI=(.005, .062)) and the churn model ($\gamma_{ch,tsXopil}$=.144, CI=(.020, .268)). A negative interaction between extraversion and tie strength is found in the smartphone adoption model ($\gamma_{sp,tsXextrav}$=-.039, CI=(-.068, -.009)). Finally, a positive interaction between commitment and tie strength is found in the phonebook adoption model ($\gamma_{pb,tsXcommit}$=.188, CI=(.058, .318)). For the sake of interpretation we simulated and plotted the hazard against the range of observed values of tie strength for different values (high, medium, low) of opinion leadership, extraversion, and commitment (Figure 4.2). Figure panels 4.2b and 4.2d show that in the smartphone adoption and churn model, tie strength has the greatest impact on social influence for opinion leaders and the impact is around zero for non-leaders. Figure 4.2c shows a similar pattern for committed customers in the phonebook adoption model. Figure 4.2a shows the opposite pattern for extraversion in the smartphone adoption model; tie strength matters most for introvert customers.

Figure 4.2: Simulated hazard rates to illustrate interactions

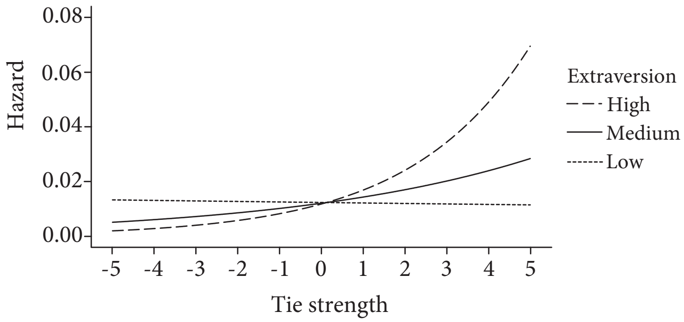
(a) Smartphone adoption (extraversion)



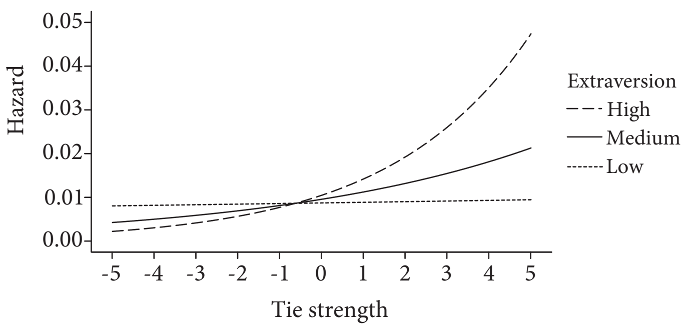
(b) Smartphone adoption (opinion leadership)



(c) Phonebook adoption



(d) Churn



4.5.5 Comparison of the impact of the determinants

We used a leave-one-out approach to determine the impact of each of the determinants on model fit. We measure the impact by the difference in the DIC (ΔDIC). Table 4.7 shows the ΔDIC values for the models without each of the three blocks. A positive ΔDIC means that the DIC increased by leaving out that particular block of variables and thus that the model fit worsened. The results show that in all three models the ΔDIC is largest for leaving out the network characteristics. These findings suggest that the network characteristics are the main determinant of social influence on behavior in customer relationships.

Table 4.7: Leave-one-out results: differences in DIC (ΔDIC)

	Smartphone	*Phonebook*	*Churn*
Without network characteristics	33.24	1.50	14.031
Without customer relationship characteristics	2.71	-4.44	-1.236
Without personal characteristics	10.37	-1.99	2.618

4.6 DISCUSSION

Marketers have high expectations regarding the use of social influence as a marketing tool. Despite the large body of research that shows that social influence shapes behavior in customer relationships, it remains unclear why some customers are more influential than others. In this study we investigate whether social influence is mainly determined by network characteristics, customer relationship characteristics, or personal characteristics. To analyze the differences between positive and negative forms of behavior we compare the impact of the determinants of social influence on adoption and churn. We study adoption across two products: a high risk product (smartphone) and a low risk mobile phone service (phonebook). We address the recent call in the literature for a shift from investigating whether social influence occurs to why it operates and why some customers are more influential than others (Godes 2011; Iyengar, Van den Bulte, and Choi 2011). On a more detailed level we investigate the effects of service usage and degree centrality. First, we will present our main conclusions and then we will discuss the theoretical and managerial implications of our work.

We find most evidence in support of the network characteristics as determinants of social influence. That is, network characteristics have a stronger impact on the model fit than personal characteristics and customer relationship characteristics. We find that in all three studied settings social influence is greater over stronger ties. The positive effect of tie strength in the phonebook adoption model is interesting because one might expect that for such a free service only simple information needs to be transferred and thus the strength of the tie would not matter (Levin and Cross 2004). An explanation could be that use of the phonebook service can not be observed by others and it is not frequently used. Therefore it is more likely to be discussed with those that are closer to the initiator which would imply a positive relationship between tie strength and social influence.

The findings on degree centrality are mixed. We find a positive effect of degree centrality on smartphone adoption and a negative effect on phonebook adoption. Based on the rationale that customers with many contacts have to divide their attention/efforts over more people one would expect a negative effect of degree centrality which is greater if the risk associated with the behavior is higher. A possible explanation for the positive effect of degree centrality is that those with large networks have a lot to lose in terms of reputation. A smartphone is a very visible product and thus if a person with a large network takes the risk of being seen with the product, the product is likely to be of high quality. This quality signal could enhance greater influence.

Homophily between the initiator and the potential followers positively affects social influence on the high risk behaviors, smartphone adoption and churn. It is important to note here that we do not claim that homophily causes one customer to influence the other to behave in a certain way (Manski 2000). We conclude that more similar customers are more likely to show similar behavior over time. This might be because consumers are more susceptible to the opinion of similar others, because they imitate similar others, or they show similar behavior independent of their relationship. We do not address the relative importance of these mechanisms and leave this for future research.

Within relationship marketing it is widely believed that firms should build and maintain strong relationships with their customers. The positive effect of commitment in the smartphone adoption model and the positive interaction with tie strength in the phonebook adoption model suggest that this is a sensible strategy also from a social influence perspective. Committed customers are more likely to influence others in case of adoption, but commitment does not stimulate nor dampen social influence when they churn. An explanation for this could be that despite the high risk of the churn decision it is not complex and does not require intense information exchange and learning. Therefore the source does not have to be committed to the firm and possess extensive information. In addition, the churn decision is based on negative information which generally has more impact than positive information regardless of the quality of the information or the source (Chen, Wang, and Xie 2011); Nam, Manchanda, and Chintagunta 2010). Another explanation could be that committed customers do not influence others to churn, because they still feel loyal towards the firm or because they feel that influencing others to churn does not fit with their (reputation of) earlier commitment to the firm.

Despite the large body of research that shows positive relationships between product involvement and opinion leadership, our results show that the effects are limited in the case of social influence on adoption and churn behavior. This is in line with the weak association between self-reported opinion leadership and sociometric leadership reported by Iyengar, Van den Bulte, and Valente (Iyengar, Van den Bulte, and Valente 2011) which implies individuals that consider themselves to be opinion leaders or involved consumers do not actually influence others more. However, we provide some evidence for a positive interaction between opinion leadership and tie strength. The positive effect of tie strength is stronger for opinion leaders than for nonleaders. In contrast to numerous studies in social psychology and marketing which have found that extraversion is positively related to opinion leadership, market mavenism, and word of mouth intentions, we do not find a main effect of extraversion on actual social influence in any of the models. There are at least two candidate explanations for this finding. First, extravert consumers might state that they will spread word of mouth, but they don't. This is related to the well-known gap between intention and behavior (Sheeran 2002). Second, extravert consumers might indeed spread word of mouth, but the word of mouth might not be effective. In our study we can not investigate which of those explanations holds. The negative interaction effect between extraversion and tie strength in the smartphone adoption model suggests that the difference between extraverts and introverts is that introverts exert more influence over stronger ties whereas tie strength does not matter for extraverts.

Our results provide evidence for the negative impact of usage on social influence. The effect of service usage on social influence is negative for complex product (smartphone) adoption. This finding is similar to the findings of Godes and Mayzlin (2009) on firm-initiated word of mouth. They argue that the potential to influence others is lower for heavy users because they are related to other heavy users. Heavy users have made up their mind on the adoption decision and are less susceptible to social influence. The correlation between the service usage of the initiators and the average service usage of the follower (per initiator) is positive and significant (.27, $p < .01$) and thus this argument may hold here.

To summarize, we find that the key determinants of social influence are the network characteristics tie strength and homophily. However, our study illustrates that also including customer relationship and personal characteristics add to social influence models. This is in line with the findings of Van Eck, Jager, and Leeflang (2011).The general conclusion is that using network data combined with actual behavior in customer relationships to investigate social influence should be favored over the use of survey data alone. Furthermore, we find differences in the determinants of social influence between products and behaviors.

4.7 MANAGERIAL IMPLICATIONS

This study provides a number of insights that are useful for marketing managers that want to incorporate social influence in their marketing strategy. We show that network characteristics are the most important determinant of social influence. This implies that to find the influentials in the customer base, managers will benefit from collecting data on the social network of their customers. Contrary to common belief we find that customers with a high degree centrality are not necessarily more influential. Managers should carefully consider the effect of these customers over a single relationship and the effect they have on the entire process. It may be that the effect on a single contact is smaller, but since they have many contacts, the total effect may be larger. The use of self-reported measures, such as opinion leadership and extraversion, for this purpose should be reconsidered. Our findings show that the effects of those measures are limited. Furthermore, we find that managers should carefully consider whether to target heavy users in the first months after the product introduction. Our results show that despite the positive effect of service usage on the adoption probability of the smartphone, the effect of service usage on social influence is negative. In other words, heavy users will adopt earlier but have less impact on consumers around them than light users. A negative effect of service usage has been found in a setting of firm-initiated word of mouth (Godes and Mayzlin 2009), but this is the first study that finds a similar effect for organic word of mouth. This makes heavy users less suitable targets for social campaigns in consumer markets, in contrast to pharmaceutical markets (e.g., Iyengar, Van den Bulte, and Valente 2011).

4.8 LIMITATIONS AND FUTURE RESEARCH OPPORTUNITIES

This study has a number of limitations which in turn provide interesting opportunities for future research. Although we compare different types of behavior and products it would interesting to investigate the determinants of social influence in a broader set of products, behaviors, and industries. That would enable formulating generalizations on the key determinants of social influence. We did not have access to other products and industries, which is a common problem in marketing research and for research on networks in particular. The telecom industry is one of the few industries for which it is relatively easy to combine network data with individual level data on behavior in customer relationships. Another limitation is related to the network data that we use. We limited ourselves to the analysis of ego networks of the initiators. Most followers will be connected to other consumers of which we have no data. We implicitly assume that the behavior is determined by the follower's characteristics and the influence exerted by the initiator. Finally, we provide some initial evidence for the interactions between personal characteristics and tie strength. These are interesting findings but require more empirical support. Furthermore, it is interesting to investigate why some of these factors, e.g., extraversion and commitment, affect the impact of network characteristics.

Chapter 5

Conclusions and Future Research

5.1 INTRODUCTION

Customer relationship marketing (CRM) is common practice in many firms today. An important aspect of CRM is explaining and predicting behavior in customer relationships by means of modeling that behavior. Recent developments in our society have had a major impact on behavior in customer relationships and the way we model it. Social networks play an increasingly important role in the lives of consumers. New technologies, such as mobile telephony, online social networks, and blogs, have enabled consumers to communicate with many others with little effort. The social network data generated by these interactions affect modeling behavior in customer relationships in two ways. First, researchers can extend the traditional models with data on the others in a customer's network. Second, models can be developed for the behavior of those in a customer's social network to assess how their behavior is affected by the behavior and characteristics of the customer.

Throughout this thesis, we have focused on modeling behavior in customer relationships from a network perspective. In this chapter, then, we provide answers to the research questions formulated in Chapter 1, summarize the main conclusions of our research in the previous three chapters, and then discuss the managerial implications of our findings. We conclude this chapter with several potential avenues for future research.

5.2 MAIN FINDINGS

5.2.1 Staying power of scoring models

In Chapter 2, we used traditional scoring models to predict individual behavior in customer relationships based on individual customer characteristics. Thus, we treated the customer as an independent decision maker. Extensive research has been done in this area, but we focused on the under-researched topic of the staying power of commonly used scoring models in order to address research question 1. We estimated a logistic regression model, a classification tree, and both in combination with a bagging procedure. The classification tree combined with a bagging procedure provided the best predictive performance. The bagging procedure improved the predictive performance of the classification trees, but there was no clear effect on the staying power. We found that the accuracy of the predictions was fairly good for the first period after the estimation period, but quickly deteriorated after that. This held for all four models we investigated. Thus, the staying power of traditional scoring models is very limited.

5.2.2 Social influence on customer behavior

In Chapter 3, we again modeled individual behavior in customer relationships, but included the behavior of the others in the network of the customer. This allowed us to assess the social influence that others exert on a customer. More specifically, we investigated the dynamics of this influence and the interaction effect between social influence and direct marketing. The social influence effect in month t is the effect of an adoption in month t-1 among a customer's contacts on the customer's adoption probability in month t. Addressing research question 2, we found that the effect of social influence decreased from the product introduction onward. Moreover, the effect of social influence was dominated by the effect of direct marketing from the fifth month after the product introduction onward. Hence, this study illustrates the importance of accounting for dynamic effects when modeling social influence on behavior in customer relationships. We did not find a significant interaction between social influence and direct marketing, which answers research question 3. Thus, the study shows that direct marketing still affects behavior in customer relationships in the current networked society.

5.2.3 Determinants of social influence

In Chapter 4, we analyzed social influence from a different perspective. We addressed research question 4 and investigated the determinants of the influence that a customer exerts on the others in his/her network. To find out why some customers are more influential than others, we combined the three prevalent perspectives on what determines social influence that have evolved in different streams of research. The determinants are network characteristics, customer relationship characteristics, and personal characteristics. Using this integrative approach, we studied the determinants of social influence across different products and behaviors. The results showed that social influence is mainly determined by network characteristics and that the impact of the determinants of social influence is product- and behavior-specific. In other words, influence is not a general customer characteristic. Furthermore, we found some evidence for a positive significant interaction between opinion leadership and tie strength, which implies that tie strength only affects social influence for opinion leaders.

5.3 MANAGERIAL IMPLICATIONS

Our findings have several implications for marketing practice. Based on the study in Chapter 2, we formulate recommendations on the use of scoring models. Our findings confirm earlier research which suggests that method does matter and that model performance is data-dependent (e.g., Neslin et al. 2006; Perlich, Provost, and Simonoff 2004). Therefore, we encourage marketers to carefully evaluate the methods they use. Calibrating different types of models on the same sample of data allows one to determine the optimal model for a specific setting. Regularly adapting the model, though, is even more important than the choice of a particular model (Leeflang et al. 2000, p. 108). With adaptation we mean that the independent variables need to be reconsidered, the data updated, and the parameters of the model re-estimated. This is because the staying power of scoring models is low, irrespective of the method. After the estimation period, the predictive accuracy deteriorates drastically. This may have serious consequences for customer lifetime value calculations and thus for the allocation of marketing budgets. Furthermore, recent calls for improving the accountability of marketing actions highlight the importance of accuracy (Verhoef and Leeflang 2009). In order to devise reliable estimates on marketing's ROI, accurate predictions of behavior in customer relationships are crucial.

Our findings regarding social influence on behavior in customer relationships have several implications for marketers who have access to network data on their (prospective) customers. The findings may be used to improve social marketing campaigns, such as referral and viral marketing campaigns, particularly with regard to the timing of these campaigns, target (or seed) selection, and use of other marketing instruments. With respect to timing, we recommend that marketers use social marketing campaigns early in the first months after the product introduction because our results show that the effect of social influence decreases over time. It seems that social influence is most powerful when there is limited knowledge in the market. With respect to the selection of seeds for a social campaign, one of the key issues is how to identify influential users in a network. We showed that network characteristics are the most important determinant of social influence. Related customers who are similar to each other are likely to show similar behavior, but this may only be partly driven by social influence. Customers who have strong relationships with others are likely to be influential and are thus good seeds for a social campaign.

Two commonly used selection criteria for influential customers are a high degree centrality and/or a high service usage level. Based on the negative effects that we found for these variables, we recommend that managers reconsider the use of these criteria. Customers with a large network have to divide their attention over many people and may exert less influence per individual. Thus, managers have to find a balance between the number of potential customers a seed can influence and the likelihood that s/he will effectively influence each of these customers. A way to investigate this is to set up an experiment and apply a different seeding strategy to different groups of customers (Hinz et al. 2011). Strategies could be based on degree centrality, usage, or the number of strong ties. In addition, one control strategy should be a random selection of seeds. By tracking the number of adoptions in each group, the effectiveness of the strategies can be assessed.

The usefulness of service usage as an indicator of influence may depend on the industry. Positive findings reported so far are mainly based on research in pharmaceutical settings where the risk associated with the new products (i.e., drugs) is extremely high and usage might indicate actual unique knowledge of a physician. In the consumer markets that we have analyzed, the positive effects no longer hold. This suggests that heavy users may not always be the best group of customers to use as seeds (Godes and Mayzlin 2009). Because of limited research on this topic, managers have to experiment with this in their own industry.

Despite the fact that we can now measure social influence and that firms are able to use their customers' social networks for marketing purposes, instruments such as direct marketing remain valuable. We find that social influence is not a substitute for direct marketing, as is sometimes suggested. Direct marketing has an independent and positive effect on behavior in customer relationships in addition to the social influence effect. More broadly, this also implies that firms do not lose or gain extra by campaigns focused on the individual customer (direct marketing) and his/her network (social campaigns).

5.4 FUTURE RESEARCH PERSPECTIVES

In this last section we provide a number of topics that we think are interesting to study in future work. In Chapter 2, we showed that the staying power of scoring models is low. We discussed several candidate explanations for this phenomenon such as missing variables and changes in the environment, but more research is needed to understand why the relevant variables and parameters change in such a short period of time. In addition to the data used in Chapter 2, data over multiple years and data on the entire market would be required. This would allow for modeling the effects of competitors' actions and trends in the market.

Given that the predictive performance deteriorates rapidly, one way to deal with this is to regularly re-estimate the static models. Another interesting option to deal with the changes that we observed involves developing dynamic scoring models (Leeflang et al. 2009) – that is, including time-varying parameters such that the model can learn over time. As soon as new data becomes available, the learning model uses the new information to update the estimates in a Bayesian manner. In the marketing literature, these dynamic models have mainly been used to model the time-varying effects of marketing instruments on sales (Ataman, Mela, and Van Heerde 2008; Van Heerde, Helsen, and Dekimpe 2007), but may be well suited for churn modeling as well.

The findings in Chapter 4 indicate that social influence is product- and behavior-specific. Given that the research on social influence is very fragmented so far (Van den Bulte 2010), we think that the field would benefit from replications of our study on the determinants of social influence in many different settings. This would allow researchers at some point to perform a meta-analysis on these studies and thereby formulate a number of generalizations. Another way to do this would be to collect data on a wide variety of products and behaviors over time, among connected individuals. Information on this connected panel could be collected in a way similar to the commonly used (representative) consumer panels. In the medical literature there are longitudinal network studies that have established social effects on behavior, for example smoking behavior (Christakis and Fowler 2008) and obesity (Christakis and Fowler 2007). The results of a longitudinal network panel study would enhance our understanding of the social influence phenomenon. The longitudinal nature of this research would also allow scholars to investigate whether interpersonal influence is becoming more and more important these days in shaping behavior in customer relationships.

Another issue that provides ample opportunity for interesting future work is the difference between organic (occurring naturally) and amplified (firm-initiated) word of mouth (Godes and Mayzlin 2009; Libai et al. 2010). Many studies, including the studies in this thesis, implicitly assume that findings on organic word of mouth can be used to stimulate firm-initiated word of mouth. There are valid arguments in favor of this assumption, because firms may use these findings to target specific customers hoping that they initiate a cascade of events, e.g., adoptions of a new product by means of organic word of mouth. However, from a customer perspective, s/he might respond differently to word of mouth knowing that it is initiated by the firm. And customers may spread different information or the same information to different contacts when stimulated to do so by a firm, because they may risk their reputation. Experimental studies in a lab or studies based on data from a natural experiment would be suitable methods to investigate these differences (Chen, Wang, and Xie 2011; Van den Bulte 2010).

In Chapters 3 and 4, we showed that social influence on behavior in customer relationships occurs and that it varies over time, individuals, behaviors, and products. Thus the behavior of a customer not only affects its value directly but also indirectly by the effect of his/her behavior on the behavior of related others. An interesting research topic is to investigate how social influence and the resulting value can be incorporated in customer lifetime value models (Kumar et al. 2010; Libai, Muller, and Peres 2009). Insights on the value of social influence allow marketers to obtain better estimates of their customers' value and thus improve their budget allocation.

In this thesis we used mobile phone data to infer networks. However, customers interact on many platforms and potentially with different groups of people on each platform (Libai et al. 2010). Given the enormous growth of online platforms, such as social media, blogs, and review sites, it would be interesting to investigate the effects of those interactions on behavior in customer relationships (Chen, Wang, and Xie 2011). A major challenge here is that the behavior of customers is not only driven by interactions but also by observational learning, which is very hard to measure. However, to fully understand behavior in customer relationships and improve the models being used, insights on these phenomena are required.

To conclude, this thesis shows the importance of including social influence in models for behavior in customer relationships. The increasing importance of social networks in our daily lives and the large amounts of data that are now available allow us to study social influence in many different settings. These developments may help us to gain a thorough understanding of the social influence phenomenon. We hope that this thesis inspires other researchers to further investigate the fascinating role of social influence in shaping behavior in customer relationships.

ENDNOTES

1. Although the company might provide other services also, the products under study here are central in the relationship and cancellation of a contract will most likely imply ending of the entire relationship. In addition, sometimes contracts are cancelled because two separate customers will begin to share the same address or two customers will get divorced. Unfortunately, the data do not allow us to distinguish those cases and hence, we treat all cancelled contracts as churn.
2. For an in-depth discussion of these methods we refer to Hastie, Tibshirani, and Friedman 2008).
3. The aim of the paper is to compare the performance of two commonly used methods and hence we used a fixed set of variables to estimate a logit model and a tree model. The resulting logit models and trees are not necessarily the same in the sense that the set of significant parameters in the logit models may differ over time and the shape of the trees may vary over time. This is a direct result of the methods used and therefore we decided to compare them this way.
4. To find the optimal value of B we used a number of values for B (50, 100, 150) and compared the results using the top-decile lift. The results for B=50 and B=100 were different and the results for B=100 and B=150 were very similar, hence we concluded that a value larger than 100 would not add much to the analysis and decided to use the value 100.
5. Based on comments of a reviewer we have also assessed the variance of the forecasts using a bootstrapping procedure (Blattberg, Malthouse, and Neslin 2009). The variance of the forecasts is rather stable over time. Hence, we decided not to discuss this explicitly. Details on this analysis can be requested from the authors.

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Samenvatting (Summary in Dutch)

Veel bedrijven houden zich tegenwoordig bezig met customer relationship management (CRM). Ze hebben ingezien dat klanten een waardevol bezit zijn en ook als zodanig behandeld dienen te worden. Een van de hoofddoelen van CRM is om waardevolle relaties met bestaande klanten op te bouwen. Bedrijven kunnen dit doen door middel van een klantretentiestrategie of een klantexpansiestrategie. Een retentiestrategie is erop gericht om klanten zo lang mogelijk aan het bedrijf te binden en een expansiestrategie is erop gericht de relatie met de klant uit te breiden door middel van cross-sell en up-sell. Bij cross-sell gaat het om het verkopen van extra producten en diensten en bij up-sell om het verkopen van een uitgebreidere en duurdere variant van het product of dienst. Voor het succesvol uitvoeren van CRM is het dus cruciaal om opzeg- en adoptiegedrag te kunnen verklaren en voorspellen. Dit geeft aan hoe belangrijk het modelleren van het gedrag in klantrelaties is in de marketingpraktijk.

Door recente maatschappelijke ontwikkelingen is het modelleren van klantgedrag aan het veranderen. In onze maatschappij zijn sociale netwerken de laatste jaren steeds belangrijker geworden. Consumenten kunnen eenvoudig communiceren met hun sociale contacten over de hele wereld door middel van mobiele telefonie, online sociale netwerken, blogs en review websites. De gegevens over deze interacties kunnen worden opgeslagen en geanalyseerd, omdat de platformen waarop deze communicatie plaatsvindt digitaal zijn. Door deze interactiegegevens te koppelen aan gegevens over klantgedrag kan de sociale invloed die klanten op elkaar hebben worden onderzocht. Deze ontwikkeling maakt het mogelijk om bestaande modellen voor klantgedrag, die gebaseerd zijn op individuele klantkenmerken, uit te breiden met een netwerkcomponent. Daarmee kan worden onderzocht in welke mate consumenten beïnvloed worden door het gedrag van de mensen in hun netwerk. Daarnaast is het mogelijk om te onderzoeken waardoor het komt dat sommige klanten veel invloed uitoefenen op de anderen om hen heen en andere klanten weinig. Deze inzichten kunnen waardevol zijn voor bedrijven en instellingen om hun (sociale) marketing campagnes te verbeteren.

In dit proefschrift beschrijven we drie studies die gaan over het modelleren van gedrag binnen klantrelaties waarbij we onderzoeken wat de rol is van de interacties tussen klanten. In hoofdstuk 2 analyseren we de houdbaarheid van een aantal veelgebruikte voorspelmodellen. We kijken niet, zoals gebruikelijk is, alleen maar naar de voorspelkwaliteit in de periode na de periode waarin de gegevens verzameld zijn, maar we kijken ook hoe goed de modellen blijven voorspellen in de perioden daarna. In hoofdstuk 3 onderzoeken we hoe het effect van sociale invloed verandert vanaf de productintroductie. Ook bekijken we of en hoe de effecten van directe marketing en sociale invloed elkaar beïnvloeden. In hoofdstuk 4 bestuderen we de determinanten van sociale invloed om erachter te komen wat de belangrijkste oorzaak is van het verschijnsel dat de een veel meer invloed heeft op zijn omgeving dan de ander. We onderzoeken dit voor verschillende vormen van gedrag en voor verschillende typen producten. Deze drie studies samen dragen bij aan de literatuur over het modelleren van klantgedrag en laten zien op welke momenten en onder welke omstandigheden consumenten elkaars gedrag beïnvloeden.

BELANGRIJKSTE RESULTATEN

In hoofdstuk 2 hebben we de houdbaarheid van verschillende churnmodellen geanalyseerd. Met de scoringsmodellen die we hebben onderzocht, wordt de relatie tussen individueel gedrag en individuele kenmerken van consumenten gemodelleerd. We hebben vier veelgebruikte modellen onderzocht, namelijk het logistische regressie model, het boommodel en beide modellen in combinatie met een bootstrap aggregatieprocedure (bagging). Met deze procedure worden de resultaten van verschillende modellen, elk geschat op een andere steekproef, gecombineerd. Het boommodel in combinatie met een baggingprocedure leverde de meest nauwkeurige voorspellingen op. Ondanks dat de voorspelkracht van de modellen beter werd door middel van de baggingprocedure hebben we geen duidelijke verbetering van de houdbaarheid kunnen vinden. In alle gevallen nam de voorspelkwaliteit behoorlijk af vanaf de tweede periode na de schattingsperiode. De belangrijkste conclusie van hoofdstuk 2 is dan ook dat de houdbaarheid van scoringsmodellen zeer beperkt is.

In hoofdstuk 3 hebben we onderzocht in welke mate het adoptiegedrag van klanten beïnvloed wordt door het adoptiegedrag van anderen in het netwerk van de klant. Dit sociale effect hebben we onderzocht door de invloed te bepalen van een adoptie in het netwerk van een klant op de kans dat de klant ook gaat adopteren. We hebben met name gekeken naar de dynamiek van het sociale effect en de interactie tussen het sociale effect en het effect van directe communicatie. We hebben gevonden dat het sociale effect afneemt over de tijd en dat dit effect gedomineerd wordt door het effect van directe communicatie vanaf de vijfde maand na de productintroductie. Dit geeft aan dat het schatten van dynamische effecten belangrijk is bij de analyse van sociale invloed op gedrag binnen klantrelaties. We hebben in deze studie geen aanwijzingen gevonden voor een interactie tussen de effecten van sociale invloed en directe communicatie. Dit geeft aan dat directe communicatie een belangrijk marketinginstrument blijft dat niet vervangen kan worden door sociale invloed.

In hoofdstuk 4 hebben we de determinanten van sociale invloed onderzocht door te kijken naar de invloed van een klant op de anderen in zijn netwerk. We hebben modellen gemaakt voor de adoptie van twee verschillende producten en voor churn. We hebben in die modellen drie groepen van determinanten van sociale invloed uit de bestaande literatuur gecombineerd. Deze determinanten zijn netwerkkarakteristieken, klantrelatiekarakteristieken en persoonskarakteristieken. We hebben gevonden dat de invloed van een klant voornamelijk bepaald wordt door netwerkeigenschappen, zoals relatiesterkte en het aantal contacten dat een klant heeft. Ook hebben we gevonden dat determinanten van sociale invloed anders zijn voor verschillende producten en voor verschillende vormen van gedrag. Invloed is dus geen algemene klanteigenschap die in elke situatie gelijk is. Tenslotte hebben we aanwijzingen gevonden voor een significant positieve interactie tussen opinieleiderschap en relatiesterkte (tussen klanten). Dit wijst erop dat relatiesterkte alleen effect heeft op sociale invloed als het gaat om opinieleiders.

IMPLICATIES VOOR DE MARKETINGPRAKTIJK

De bevindingen van dit proefschrift zijn niet alleen relevant voor de marketingwetenschap, maar ook voor de praktijk. Allereerst vinden we dat de voorspelkracht van de verschillende churnmodellen varieert en daarom is het belangrijk dat er voor elke specifieke situatie onderzocht wordt welk model het beste voorspelt. Naast de keuze voor een bepaald model is het ook belangrijk om het model regelmatig opnieuw te schatten, omdat we laten zien dat de houdbaarheid van alle onderzochte scoringsmodellen beperkt is. Dit betekent dat er regelmatig moet worden onderzocht welke onafhankelijke variabelen er in het model moeten worden opgenomen, dat er nieuwe data moeten worden verzameld en dat de parameters opnieuw geschat moeten worden. Deze maatregelen zorgen ervoor dat de churnvoorspellingen accurater worden. Dit is belangrijk voor het selecteren van de juiste klanten om te benaderen en voor het uitvoeren van betrouwbare klantwaardeberekeningen. Deze berekeningen zijn op hun beurt weer belangrijk voor de toewijzing van marketingbudgetten en het uitdrukken van de uitkomsten van marketinginspanningen in financiële termen.

Onze resultaten op het gebied van sociale invloed op gedrag binnen klantrelaties hebben verscheidene implicaties voor marketeers die beschikken over netwerkgegevens. Hiermee kunnen sociale marketingcampagnes, zoals aanbevelings- en virale campagnes, verbeterd worden. We doen aanbevelingen over de planning van sociale campagnes, de selectie van de juiste klanten en het gebruik van marketinginstrumenten.

Wat betreft de planning raden we aan om sociale campagnes met name in te zetten vlak na de productintroductie omdat vanaf dat moment het sociale effect afneemt. Als de tijd vordert en meer algemene kennis over het nieuwe product wordt opgebouwd in de markt, wordt sociale invloed minder sterk. Bedrijven kunnen dan beter relatief meer gebruik maken van directe communicatie. Het effect van directe communicatie blijft namelijk constant over de tijd.

De selectie van klanten is belangrijk en het is zaak om die mensen te selecteren die veel invloed uitoefenen op de anderen in hun omgeving. Ons onderzoek laat zien dat daarbij met name gekeken moet worden naar netwerkeigenschappen. Klanten die sterke relaties hebben met anderen in hun netwerk hebben meer invloed en zijn dus goede kandidaten voor een sociale campagne. Voor twee veelgebruikte maatstaven van invloed, graad (het aantal mensen waar een klant direct mee communiceert) en servicegebruik, vinden wij gemengde resultaten en daarom is het belangrijk dat marketeers onderzoeken of in hun industrie deze twee maatstaven wel geschikt zijn om invloedrijke mensen te identificeren. Voor graad vinden wij negatieve effecten op sociale invloed. Klanten met veel contacten kunnen wel veel anderen bereiken, maar de invloed die ze per contact uitoefenen is vaak kleiner. Tussen deze twee effecten moet een balans gevonden worden door bijvoorbeeld het uitvoeren van experimenten. De positieve effecten van servicegebruik op invloed zijn voornamelijk beschreven in een farmaceutische context. In de consumentenmarkt die wij hebben bestudeerd, vinden we deze positieve effecten niet. Servicegebruik kan daarom niet zomaar in alle situaties als indicator voor invloed worden gebruikt. Vanwege het beperkte aantal studies zullen marketeers zelf moeten experimenteren om te kijken of servicegebruik een goede indicator voor invloed is.

We hebben in ons onderzoek geen interacties gevonden tussen directe communicatie en sociale invloed. Het is dus niet zo dat directe communicatie en sociale invloed elkaar verzwakken, zoals vaak wordt gesuggereerd. Beide hebben een onafhankelijk en positief effect op gedrag binnen klantrelaties. Marketeers zullen ook hier een balans moeten vinden tussen het gebruik maken van sociale invloed en de inzet van directe communicatie bij het opstellen van hun marketingstrategie.