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Understanding the Role of Acquisition and Retention Effects

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Chapter 1

Introduction

1.1 CUSTOMER RELATIONSHIPS

Customers are valuable assets for firms (Kumar, Lemon, and Parasuraman 2006), but developing relationships with them can be effortful. In the development of customer relations firms could focus on customer retention (including cross-selling) and/or customer acquisition. Retaining customers, i.e. developing long term relationships with customers, offers major benefits to firms, such as improved customer value (Jain and Singh 2002) and lowered acquisition costs (Farquhar 2005). Yet, acquisition yields larger customer volumes and a possible base to grow in the short run. In this thesis we focus on both the valuation of retained customers and budget allocation decisions between customer acquisition and customer retention. In the remaining part of this introductory chapter we will introduce the topics that are covered in this thesis. In section 1.2 we introduce the customer value concept. Section 1.3 provides a short discussion on the tension between acquisition and retention. In section 1.4 our key research questions and objectives are formulated. Section 1.5 describes the setting of our research. The main theoretical and managerial contributions are presented in sections 1.6 and 1.7, respectively. Finally, we provide an outline of the thesis in section 1.8.

1.2 CUSTOMER VALUE

In the past decade, customer lifetime value (CLV) -i.e. the net present value of each customer (Gupta et al. 2006; Rust, Lemon, and Zeithaml 2004)- has become increasingly important as a marketing metric (e.g., Venkatesan and Kumar 2004; Verhoef, Van Doorn, and Dorotic 2007). Moreover, recently Kumar and Shah (2009) have shown that implementing customer value based decision making may improve firm value. A basic CLV model computes the profit of a customer in a certain time period for each expected time period the customer has a relationship with the firm (Berger and Nasr 1998; Bolton, Lemon, and Verhoef 2004). The impact of a change in retention on CLV is substantial (Gupta, Lehmann and Stuart 2004). In addition, a CLV model could also incorporate cross-sell (Donkers, Verhoef, and De Jong 2007), marketing costs (Venkatesan and Kumar 2004), service costs (Niraj, Gupta, and Narasimhan 2001) and credit risk (Zhao, Zhao, and Song 2009). All these components add to a better prediction of CLV per customer.

Not only can we identify an increase in scientific studies on CLV, the use of CLV in firms also increased rapidly in the past decade. Many firms went, or are still going, through a development of CLV from a measurement instrument to a policy making tool. In the earliest stage of CLV implementation at companies, CLV was computed by subtracting costs from revenues. After that firms started to predict CLV, for example by predicting churn and future revenues, enabling computations of future customer value, with or without the inclusion of campaign simulations. And, in its most advanced form, companies are trying to influence the CLV of customers by identifying the most suitable marketing strategy for each customer and acting upon this.

1.3 TENSION BETWEEN ACQUISITION AND RETENTION

Acquisition and retention activities are related in several ways, sometimes leading to serious tension (Sirohi et al. 1998). First of all, since resources are limited (Rust, Lemon and Zeithaml 2004), acquisition and retention spending are correlated by budget constraints (Berger and Nasr-Bechwati 2001). In other words, companies should choose whether to spend their budgets on either acquisition, or retention, or a mix of both. Secondly, the marketing strategy that is used to acquire customers affects the future value (including retention probability) of these new customers (Gupta and Zeithaml 2006). Research has shown, for example, that the use of price promotions to acquire new customers, results in switch-prone, hardly retainable customers (Anderson and Simester 2004; Lewis 2006; Musalem and Joshi 2009). Finally, it is also possible that acquisition strategies not only affect new customers, but also influence the consumers that are current customers of a company. Even though these acquisition campaigns are not aimed at existing customers, these customers may be aware of the existence of acquisition campaigns and their behavior may be influenced by this mere fact (Novo 2005).

1.4 RESEARCH FRAMEWORK

In the studies that have been performed, customer value and acquisition and retention issues form the main topic. The chapters fit in a framework which is summarized in Figure 1.1. As can be seen in Figure 1.1, Chapter 2 examines the CLV of retained customers, not taking into account any acquisition issues. Chapter 3 does include acquisition by examining the effect of acquisition on the value of retained customers. Chapter 4 looks at the interplay between all three dimensions, i.e. the way in which acquisition, retention, and CLV are influenced by and are influencing each other. All three studies are empirically tested in the Dutch energy market. With this framework and the three studies we address our main research objective:

To understand customer (lifetime) value in the energy market.

In line with this objective, we define three research questions:

1) *How can CLV be predicted; and how can we use these predictions to identify the most suitable marketing action per customer?*
2) *What is the effect of attractively priced acquisition campaigns on the retention intention of existing customers?*
3) *How do above-the-line (ATL) and below-the-line (BTL) communication influence acquisition and retention profitability?*

The research questions are answered in the three core chapters of this thesis. In Chapter 2 we develop a CLV model that includes revenues, costs and credit risk of the customer relationship. Through simulations of different marketing actions we propose the most suitable marketing action for each customer. Chapter 3 looks at the effect of acquisition campaigns on existing customers' relational intentions. First, we investigate the effect of being aware of attractively priced acquisition campaigns on retention intention. Then, we identify other explanatory variables that help us explain the relationship between awareness and retention intention. Finally, we calculate the CLV consequences of existing customers' awareness of acquisition campaigns. In Chapter 4 we elaborate further on the balance between acquisition and retention by estimating a Vector Autoregressive (VAR) model in order to 1) investigate the relation between retention and acquisition profitability and 2) examine how retention and acquisition profitability are influenced by marketing communication. The result of this chapter is a framework that opens up the possibility of predicting in advance what the long term effect of certain strategies will be on new and existing customers.

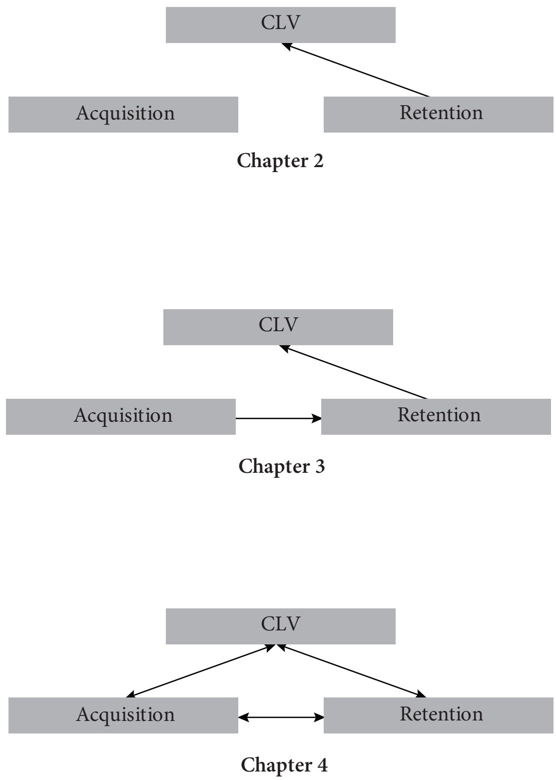


Figure 1.1: Framework of the core chapters of this thesis

1.5 ENERGY MARKET

All three studies are empirically tested in the Dutch consumer energy market. Since the liberalization in 2004, a change occurred from a field with local monopolies (Van Damme 2005) to a market with intensified competition (Wieringa and Verhoef 2007). As much as 33% of the Dutch consumers have indicated they changed energy suppliers since July 2004 (Energiekamer NMa 2011), and this number is still increasing (Energeia 2012). This new market situation required a radical change in the way energy suppliers have to deal with customers, and calls for a deeper understanding of customer behavior. We focus on the customer behavior of customers of a large incumbent energy supplier. The rich databases of the focal company enable us to estimate extensive models.

In addition, the new market environment caused an increase in marketing expenditures (Sullivan and Sheffrin 2002). The main reason for customers to switch in the energy market is the attractive price that is offered to prospective customers (Meijer and Perfors 2004a, 2004b; Pomp, Shestalova, and Rangel 2005, the focal company's exit-survey 2009). These attractively priced campaigns are often promoted through mass media or through personal selling methods. This active use of marketing channels makes the energy market, as it is currently functioning, an adequate study context for examining several aspects of both customer acquisition and customer retention. Hence, the Dutch energy market, and the focal supplier in particular, provide a very appropriate setting for gaining insights into our research questions.

1.6 THEORETICAL CONTRIBUTION

With this thesis we contribute to the literature on customer relationship management. The CLV prediction model we present in Chapter 2 is the first to include credit risk as a major component of customer value. In addition, we developed and applied a framework for applying the high-valued CLV metric (e.g., Gupta, Lehmann, and Stuart 2004; Gupta et al. 2006; Kumar and Shah 2009; Rust, Lemon, and Zeithaml 2004) in an actual business setting.

The view at the relation between customer acquisition activities and customer retention we presented in Chapter 3 fills a research gap. Whereas prior studies have linked acquisition to retention either cross-sectionally, by distributing resources over these two stages in relationship marketing at one point in time (e.g. Berger and Nasr-Bechwati 2001;

Blattberg and Deighton 1996; Reinartz, Thomas, and Kumar 2005); or with a longitudinal view, by examining the future value of prospective customers after these same customers have been acquired (e.g. Lewis 2006; Thomas 2001); we examined the effect of acquisition campaigns on consumers that are current customers of the acquiring company.

Our examination of the effect of marketing resource allocation on the interplay between acquisition and retention profitability in Chapter 4 combines several aspects that have been presented by different studies. Especially the inclusion of both above-the-line and below-the-line marketing, as well as the profitability of both acquired and retained customers, while also considering the mutual relations between these aspects and accounting for competitive expenses, yields new theoretical insights.

1.7 MANAGERIAL CONTRIBUTION

The aim of all three studies in this thesis is to provide insights into issues that are directly applicable in marketing practice. In all studies, the research question was based on real-life questions of the focal company. Therefore, the results should provide the managers with valuable insights. With our customer value study we present a means to know in advance whether a chosen action will or will not add value to the customer base. Managers can use this information to identify which customers should be targeted with what action. Knowing how acquisition activities influence existing customers' CLV gives managers the possibility to asses whether or not an acquisition campaign will decrease the value of the customer base. This knowledge can be used in the decision to launch an acquisition campaign and, if necessary, to take appropriate countermeasures if campaigns are introduced. Finally, understanding how acquisition spending is related to retention spending and how to influence this relationship by marketing campaigns provides managers with a tool for budget allocation. This tool opens up the possibility of predicting in advance what the long term effect of certain strategies will be on new and existing customers.

1.8 OUTLINE OF THE THESIS

In Chapter 2 we present a customer value model that includes revenues, service costs and credit risk of the customer relationship and show how this model can be used for marketing decision making. In Chapter 3 of this thesis we study the effect of acquisition campaigns on existing Customers' CLV. Chapter 4 assesses the effect of above-the-line and below-the-line communication on acquisition and retention profitability. In Chapter 5, we give a summary of the main findings of the studies described in Chapters 2, 3, and 4. Then we suggest managerial implications, and propose avenues for future research.

Chapter 2

Customer value modeling in the energy market and a practical application for marketing decision making

2.1 INTRODUCTION

In the past decade there has been an emerging stream of literature on customer lifetime value (CLV) (Gupta et al. 2006; Hogan, Lemon, and Rust 2002; Rust, Lemon, and Zeithaml 2004; Verhoef and Donkers 2001). CLV, i.e. the net present value of each customer, has become increasingly important as a marketing metric (e.g., Donkers, Verhoef, and De Jong 2007; Venkatesan and Kumar 2004; Verhoef, Van Doorn, and Dorotic 2007). Moreover, recently Kumar and Shah (2009) have shown that implementing customer value based decision making may improve firm value.

A basic CLV model computes the profit of a customer for each expected time period the customer has a relationship with the firm (Berger and Nasr 1998; Bolton, Lemon, and Verhoef 2004). Several variations to this basic model can be found in the marketing literature. Many of these variations include the prediction of retention and profit as components, where profit is usually limited to the prediction of revenues/margins and (direct) marketing costs (e.g., Venkatesan and Kumar 2004). Table 2.1 gives an overview of CLV models that can be found in marketing literature, and shows which components have and have not been included in CLV models so far. Most models include at least retention and profit. Gupta, Lehmann and Stuart (2004) find that the impact of a change in retention on CLV is very important, whereas Donkers, Verhoef, and De Jong (2007) show that retention probabilities should not be viewed without considering cross-buying needs. Apart from retention and revenues, many models include marketing costs, meaning direct sales and acquisition costs (e.g., Venkatesan and Kumar 2004). Niraj, Gupta, and Narasimhan (2001) were one of the few incorporating service costs, claiming that the logistic and operation costs of buying, storing, and selling are typically as important as, if not more important than, direct marketing costs. Since incoming cash flows from customers may be at stake when the bills are not paid, the inclusion of credit risk to CLV models seems rather important. However, studies relating credit losses to customer profitability are very rare. Zhao, Zhao, and Song (2009) linked credit risk to profit, but this study did not take into account any of the other CLV components. Schulze, Skiera and Wiesel (2012) find that linking customer metrics to shareholder value without considering debt leads to biased estimates of customer equity. Although incorporating many components, their study does not predict customer value at the individual customer level.

The first objective of this chapter is to develop a CLV model that includes the abovementioned components, and can be used in a contractual service setting, i.e. a setting in which both the firm (by committing itself towards delivering the service) and the customer (by committing itself towards paying the bills) have obligations towards each other during a longer period of time. Unlike most previous studies, we do not only include profits resulting from the customer relationship through retention, cross-buying, etc. as revenues, but we also take into account service costs and credit losses, which consists of credit risk and payment enforcement costs.

The cost side of the CLV equation has been underexposed due to challenges concerning the complexities and subtleties of cost modeling (Gupta et al. 2006). These challenges are mainly related to insufficient data availability and the inability of companies to allocate costs at the customer level. In this chapter we deal with these cost issues, by estimating models for service and payment enforcement costs. In addition, we include a model for credit risk, because revenues only count once they are actually paid by the customer.

Secondly, although CLV is identified as an important metric for firms, managers may experience difficulties implementing it. Of special interest is the question how customer value can be used to improve marketing decision making. Hence, the second objective of this chapter is to develop a framework that shows how customer value prediction can be used in marketing decision making. We do so by simulating the effect of several changed model inputs, which are presumably caused by marketing actions, on the value of each customer. These simulations allow a firm to determine the most suitable marketing action for each customer.

Table 2.1: Overview of studied components in CLV models

Study	Context	Aggregate vs individual level data	Retention	Profit	Cross-sell	Service costs	Credit losses	Marketing costs
Reinartz & Kumar (2000)	Non contractual setting	individual	X	X				X
Niraj et al.(2001)	Supply chain	individual		X		X		
Gupta, Lehman & Stuart (2004)	High growth industry	aggregate	X	X				
Bolton, Lemon & Verhoef (2004)	Service organizations	aggregate	X	X				
Rust, Lemon & Zeithaml (2004)	Airlines	individual	X					
Venkatesan & Kumar (2004)	B-to-B	individual	X	X				X
Donkers, Verhoef & De Jong (2007)	Insurance industry	individual	X	X	X			
Petersen & Kumar (2009)	B-to-C retailer	individual		X				X
Kumar & Shah(2009)	B-to-C retailer* B-to-B	individual	X	X				X
Zhao, Zhao & Song (2009)	Creditcard industry	individual		X			X	
Schulze, Skiera & Wiesel (2012)	Several industries	aggregate	X	X		X	X	X
This study	Energy market	individual	X	X	X	X	X	

This study contributes to the existing literature on CLV as follows. This is the first study to include credit risk as a major component of CLV. Our second contribution is that we show how firms could, in a relatively comprehensive manner, apply insights from their CLV models to improve the CLV of their customer base. As this study has been executed in very close cooperation with the studied energy supplier, we have developed and applied a framework for applying the CLV metric (e.g., Gupta, Lehmann, and Stuart 2004; Gupta et al. 2006; Kumar and Shah 2009; Rust, Lemon, and Zeithaml 2004) in an actual business setting.

The remainder of this chapter is organized as follows. We first construct a customer value model. After validating the model and assessing the relevance of the model components, we simulate the value effects of several marketing actions. To end with, we show how these simulations can be used to identify the most suitable action per customer.

2.2 BUILDING A CLV MODEL

As a result of a shift in marketing focus from products to customers (Hanssens, Leeflang, and Wittink 2005) CLV has become increasingly important. CLV takes into account the long-term consequences of actions (Hoekstra, Leeflang, and Wittink 1999) and can be used to identify profitable customers and allocate resources accordingly (Kumar and Reinartz 2006). In order to make a CLV model, we take several steps. First of all, we identify what customer behavior influences value, i.e. we determine relevant CLV components. Secondly, we determine which predictors can be used for the prediction of CLV components. After the components and the predictors have been identified, we estimate a model for predicting the value of each CLV component. Finally, the component models are combined into a CLV model that gives us a predicted CLV per customer.

2.2.1 Determining relevant CLV components

A CLV model computes the sum of profit (revenues minus costs) of a customer (i) in a certain time period (t), divided by a discount rate (d), for each expected time period the customer has a relationship with the firm (Berger and Nasr 1998; Bolton, Lemon, and Verhoef 2004). Kumar, Lemon, and Parasuraman (2006) note that it is important to examine the context for which a CLV model is built and then decide on whether the CLV model should be at the segment-level versus the individual customer-level, and whether it should be static or dynamic. Gupta and colleagues (2006) put forward some challenges concerning costs, by stating that marketers seem to have a good grasp of the revenue issues , whereas they frequently ignore the complexities and subtleties of the cost and risk side of the equation. In our CLV model we include components that were previously studied (see Table 2.1) and/or seem applicable in our study context. Figure 2.1 shows our conceptual CLV model. According to this model, CLV is the result of retention, revenues, credit losses (credit risk and payment enforcement costs) and service cost. Revenues (gross profit) of retained customers create value, but only if the customer really pays the bills, i.e. if the credit risk is low. Increased credit risk may lead to increased volatility of incoming cash flows from customers. In addition, if the bill is not paid, payment enforcement costs will be incurred, making the credit losses even larger. As a consequence, it is important for firms to understand the importance of credit risk in customer valuation. Service costs are associated with delivering service to customers (Niraj, Gupta, and Narasimhan 2001) -e.g. the costs of providing customer care through a call center or website- and reduce a customer's value. An important characteristic of all variables that are included in our CLV model is that they capture the behavior of customers. Hence, marketing (action) costs were not included, because these costs represent firm behavior instead of customer behavior.

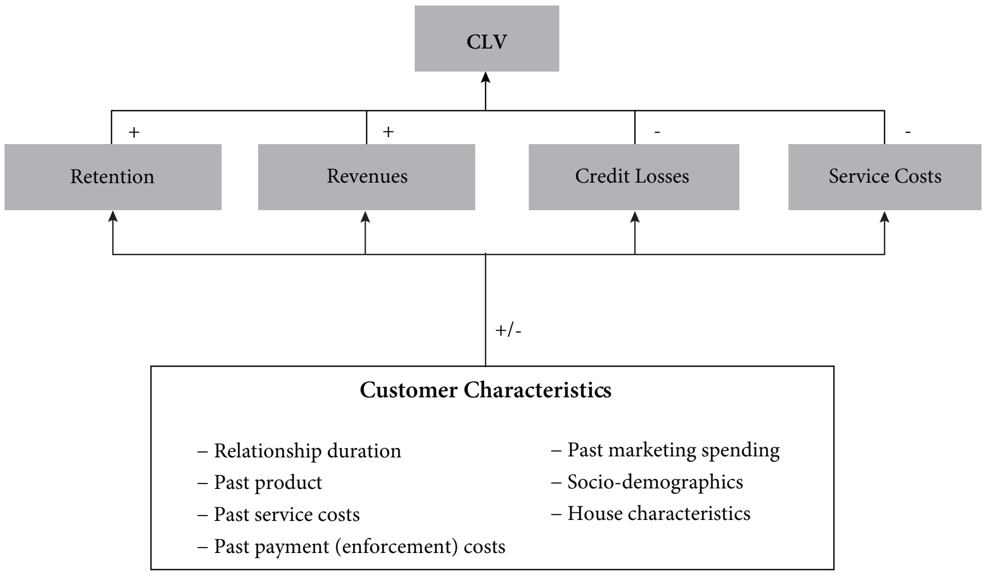


Figure 2.1: Conceptual CLV model

2.2.2 Predictors of CLV components

Now that we have identified the components of our CLV model, we determine which variables can be used for CLV component prediction (the lower part of Figure 2.1). In general, past customer behavior often is a good predictor for future customer behavior (Kumar and Reinartz 2006). Hence, the set of predictors should include past behavior on the value components, i.e. past revenues (product possession and usage), past service costs, and past credit losses. The inclusion of the past values of the CLV components, i.e. past revenues, past credit losses, past service costs, covers a possible effect the components may have on each other.

In addition, the inclusion of other relationship characteristics, such as relationship duration, payment method, and customer moving information seems feasible.

Apart from customer relationship characteristics, the inclusion of socio-demographic variables as predictors ensures that heterogeneity between customers is accounted for (Leeflang and Wittink 2000). Socio-demographic characteristics could include information on marital status, number of children in a household, age of the breadwinner, social class, an indication for possession of a car, donation to charity, buying on credit and use of internet.

Finally, since we are developing a model for the energy market, and energy usage is related to the type and size of the house a customer lives in, we should include housing characteristics. Characteristics of the house include information on the square footage and value of the house and its year of construction. Apart from the relation between housing characteristics and energy usage, housing characteristics also account for heterogeneity between customers.

2.2.3 Modeling CLV

The four components, as identified in section 2.2.1 are included in the CLV model. In CLV models that predict value for more than a year ahead, a discount factor is added because money in the future is worth less than money right now. However, in our model –both due to limited data points and to the fact that marketing decisions are hardly ever taken more than one year in advance- our time horizon is only one year. Hence, in our study CLV is actually CV, and is the result of predicted retention, revenues, credit losses and service costs for the next year (t):

$$CV_{it}=Retention_{it}*(Revenues\ *(1-CreditRisk_{it})-PaymentEnforcementCosts_{it}-ServiceCosts_{it}) \quad (2.1)$$

2.2.3.1 Retention

The first CV component we model is retention, which is defined as the probability that a customer (i) will still be a customer next year. Through a churn modeling contest, Neslin and colleagues (2006) showed that binomial logistic regression is a very useful method for modeling retention, due to its relative simplicity and superior predictive capacities. Therefore, we choose this method for prediction of retention. For our CV model, we estimate the following retention model:

$$P(Retention_{it}=1)=\frac{exp(\alpha_0+\alpha_c Relation_{cit}+\alpha_s SocioDemo_{sit}+\alpha_h House_{hit})}{1+exp(\alpha_0+\alpha_c Relation_{cit}+\alpha_s SocioDemo_{sit}+\alpha_h House_{hit})} \tag{2.2}$$

where

- $Relation_{cit}$ are the customer relationship characteristics of customer *i* at time *t*;
- $SocioDemo_{sit}$ represent the socio-demographic characteristics of customer *i* at time *t*;
- are the characteristics of the house customer *i* lives in at time *t*;
- $House_{hit}$ is a vector of parameter estimates for relationship characteristics, being: PaymEnforcement t-1, Service t-1, Relationship Duration, Electricity usage, Gas usage, Dual Fuel, Electricty Product, Gas Product, Marketing effort t-1, Upsell t-1, Cross-sell t-1, Direct Debit, Moving Indicator t-1, and Former Monopolist;
- α_s is a vector of parameter estimates for socio-demographic characteristics, containing: Marital Status, Number of Children, Age Head of Household, Social Class, Owns a car, Gives to charity, Buys on credit, and Buys on Internet;
- α_h is a vector of parameter estimates for housing characteristics, which include: House Type, House Value, House Surface, and House Construction Year.

2.2.3.2 Revenues

In the energy market revenues are a function of the product a customer possesses, the gross contribution of that particular product and the energy usage for that product:

$$Revenues_{it}=\sum_{j=1}^{J}[GC*SYU_{ji}*P(Product_{it}=j)] \tag{2.3}$$

where

- GC_j is the gross contribution1 per product;
- SYU_{ij} is the standard yearly electricity or gas usage2, which indicates the expected amount of electricity or gas customer *i* uses in a year;

- $P(Product_{it}=j)$is the probability that customer *i* posseses product *j* next year (t). Product possession is estimated for gas and electricity separately, where "no electricity" and "no gas" are used as base cases, and customers can have only one electricity and/or one gas product:

$$P(Product_{it}=j)=\frac{exp(\beta_0+\beta_c Relation_{cit}+\beta_s SocioDemo_{sit}+\beta_h House_{hit})}{\sum_{j=1}^{J} exp(\beta_0+\beta_c Relation_{cit}+\beta_s SocioDemo_{sit}+\beta_h House_{hit})} \quad (2.4)$$

  where β_c, β_s, β_h are vectors of parameter estimates for relationship, socio demographic and housing characteristics, respectively (see Equation 2.2).

2.2.3.3 Credit losses

Credit losses consist of payment enforcement costs and credit risk. Payment enforcement costs are the costs that are charged for not paying the bill. Customers that do not pay the bill first receive a reminder, then a dunning and then a collection. For each step of payment enforcement, costs are added to the total payment enforcement effort. Since a single failure to pay is most likely just an accident, e.g. a customer who forgot to pay his bill in time because of long holidays, we attribute the overall payment enforcement costs to those customers that receive more than one enforcement attempt[3]:

$$PaymentEnforcementCosts_{it}=P(PaymentEnforcement_{it}=1)*C_{PaymentEnforcement} \quad (2.5)$$

where

- $P(PaymentEnforcement_{it})$ is the likelihood that customer *i* receives more than one payment enforcement attempt in period *t*:

$$P(PaymentEnforcement_{it}=1)=\frac{exp(\gamma_0+\gamma_c Relation_{cit}+\gamma_s SocioDemo_{sit}+\gamma_h House_{hit})}{1+(\gamma_0+\gamma_c Relation_{cit}+\gamma_s SocioDemo_{sit}+\gamma_h House_{hit})} \quad (2.6)$$

  where γ_c, γ_s, γ_h are vectors of parameter estimates for relationship, socio demographic and housing characteristics, respectively (see Equation 2.2);
- $C_{PaymentEnforcement}$ are the average costs per payment enforced customer, which are fixed over time.

Credit risk represents the probability that a customer will not pay the bill. The prediction of credit risk is based on the probability that the company needs to hire a collection agency to cash the bills[4], i.e. the collection stage in the payment enforcement process. We found that 85% of the customers that are approached by a collection agency eventually pay the bill. Hence:

$$P(Credit\ risk_{it}{=}1){=}P(Collection_{it}{=}1)^{*}C(1{-}085) \tag{2.7}$$

where

- $P(Collection_{it})$ is the likelihood that customer i is contacted by a collection agency in period t:

$$P(Collection_{it}{=}1){=}\frac{exp(\delta_0{+}\delta_c Relation_{cit}{+}\delta_s SocioDemo_{sit}{+}\delta_h House_{hit})}{1{+}exp(\delta_0{+}\delta_c Relation_{cit}{+}\delta_s SocioDemo_{sit}{+}\delta_h House_{hit})} \tag{2.8}$$

  where δ_c, δ_s, δ_h, are vectors of parameter estimates for relationship, socio demographic and housing characteristics, respectively (see Equation 2.2).

2.2.3.4 *Service costs*

Service costs are associated with delivering service to customers, e.g. the costs of providing customer care through a call center or website; and reduce a customer's value. In our application, service costs mainly consist of inbound contact costs. Most customers never contact a company. The customers that do seek contact, can do so only once, or more often. The number of contacts per contacting customer could depend on either the characteristics of a customer, or the way in which a problem is solved by the company, e.g. if the company does not really solve the problem during the contact, the customer will call again. Since it is hard to determine what causes repeat calling, we decided not to model the number of inbound contacts per customer, but merely the contact incidence:

$$ServiceCosts_{it}{=}1){=}P(Service_{it}{=}1)^{*}C_{Service} \tag{2.9}$$

where

- $P(Service_{it}{=})$is the likelihood that customer i contacts the call center in period t:

$$P(Service_{it}{=}1){=}\frac{exp(\theta_0{+}\theta_c Relation_{cit}{+}\theta_s SocioDemo_{sit}{+}\theta_h House_{hit})}{1{+}exp(\theta_0{+}\theta_c Relation_{cit}{+}\theta_s SocioDemo_{sit}{+}\theta_h House_{hit})} \tag{2.10}$$

  where θ_c, θ_s, θ_h are vectors of parameter estimates for relationship, socio demographic and housing characteristics, respectively (see Equation 2.2);
- $C_{service}$ are the average costs per contacting customer, which are fixed over time.

2.3 EMPIRICAL APPLICATION

The CV model as described in the previous sections is applied at a large incumbent energy supplier. The rich databases of this supplier allow for the estimation of the proposed CV model. This company collected and stored huge amounts of information on customer behavior since liberalization of the energy market. The information includes relationship characteristics, socio-demographic characteristics and characteristics of the house the customer lives in.

The socio-demographic and house characteristics stem from an external data source. The relationship characteristics are registered customer behavioral facts. Retention is measured as being active at January 1st 2007 and still being there at January 1st 2008; which implies that both customers that moved out but have not moved back in, and customers that changed suppliers and joined a competitor are not retained. The way in which competitors approach movers versus customers that do not move may differ, but the result is the same, i.e. the customer is not retained. Product possession is based on the product a customer has at January 1st 2007; in general, customers are most likely to switch products when they are confronted with a specific product offer (either in a targeted or not-targeted campaign). Since many customers are acquired at special (low) price products, which are not so profitable, energy suppliers will try to make an up-sell to a higher priced product by the end of the first year contract. Electricity and gas usage are estimated in advance for a whole year. Customers receive monthly bills for one twelfth of the estimated usage; by the end of the year, the actual usage is compared with the total of the monthly bills and the difference is settled. Since it is both in the interest of the customer and the supplier, the estimated usage is as accurate as possible and hardly ever changes, i.e. is constant for several years, hence standard yearly usage. The payment enforcement attempts, i.e. reminders, dunnings and collections, are counted over a year. Every time the monthly bill is not paid the payment enforcement process is started up. Service costs are a count of the number of contacts over a year: every time a customer contacts the customer contact center, either by phone, letter, fax, or e-mail one contact is counted.

We have this information for all 1.8 million customers that were active on January 1st 2007. For the estimation of the CV model we use a random sample of 0.9 million customers. Descriptive statistics of the most important relationship characteristics of this sample[5] can be found in Table 2.2.

Table 2.2: Descriptive statistics

Variable**	Mean	Std dev	Minimum	Maximum
SYU (usage) electricity*	3183	1491	1	10000
SYU (usage) gas*	1704	875	1	10000
Relationship duration (mnths)	54	15	0	73
Number of marketing contacts	1.5	1.4	0	10

Variable**	% dataset
Retained customers (in 2007)	92%
Electricity product	
Regular	56%
Special 1	15%
Special 2	7%
Special 3	5%
Special 4	12%
No electricity	5%
Gas product	
Regular	69%
Special 1	5%
Special 2	8%
No Gas	18%
Customers with service costs	28%
Customers with payment enforcement	16%
Customers with credit risk	4%
Upsell	7%
Cross-sell	1%
Customers having both electricity and gas	78%
Customer paying with automatic payment	82%
Moved customers	6%
Customer living in former monopolistic area	97%

* Both electricity and gas usage have been limited to 10k, since higher values in the consumer market are most likely measurement errors. Average usage only computed for those customers that have an active electricity or gas contract, respectively.

** Number of marketing contacts, customers with service costs, customers with payment enforcement, customer with credit risk, upsell, cross-sell, moved customers are measured from January 1st 2006 to January 1st 2007; electricity and gas usage and products, relationship duration, customer having both electricity and gas, customers paying with automatic payment and customers living in former monopolistic area are measured at January 1st 2007.

2.4 RESULTS

All component models have been estimated. The most important findings are discussed in section 2.4.1. After establishing the validity of the individual component models (Section 2.4.2), we assess the predictive validity of our complete CV model (Section 2.4.3), and examine the relevance of each component to the overall CV prediction (Section 2.4.4).

2.4.1 Estimation results

Most resulting parameters of each component model are intuitively in the correct direction[6]. In general, the relationship characteristics exert the largest influence on the prediction of each of the components. For retention we find a significant influence of possession of fixed term products, i.e. customers that have a three-year contract are more likely to be retained in the next year. Furthermore, customers with payment problems and customers that recently moved are less likely to be retained.

Revenues, i.e. (in the context of the energy market) product possession, is highly related to product possession in the previous year. As expected, having a specific product in the previous period increases the probability of having the same product in the current period. In addition, if customers decide to change products, those customers with special products are more likely to switch to another special product (as opposed to switching to the regular product). This may indicate that some customers are generally more deal-prone than others.

Both credit losses and service costs are largely influenced by last year's behavior on these same components. Both payment enforcement costs and credit risk are expected to be higher when customers had payment problems in the previous year. Another good indicator of credit losses are characteristics related to relationship duration: new customers (especially new customers who regularly changed energy suppliers) are more likely to have payment problems. Service costs are most likely to occur for customers who contacted the company last year, customers with payment problems and customers who recently switched products.

2.4.2 Predictive performance of component models

Since our CV model consists of several sub-models, the component models, we first assess the predictive performance of each individual model. The predictive performance of the component models can be assessed with the Top Decile Lift (TDL). The TDL indicates the percentage of customers with a certain component value (e.g. customers that stayed, or customers with payment enforcement costs) in the top 10%, divided by the percentage of customers with a certain component value in the whole population (e.g., Lemmens and Croux 2006; Neslin et al. 2006). So, if the TDL equals 1, the model predicts just as well as a random assignment of customers to a condition. A higher TDL, indicates a better model performance. However, for samples in which the actual occurrence of an event is high -e.g. 90% of the customers is in situation A- the TDL will hardly ever be much larger than 1. In this case, assigning all customers to situation A results in a correct prediction of A in 90% of the cases. Even if the model predicts well -e.g. in 92% of the cases- the improvement of the model over the random assignment of customers is small.

Table 2.3: TDL and hit rate

	TDL 2007	TDL 2008	Hit rate 2007	Hit rate 2008
Retention	1.04	1.04		
Revenues				
Electricity			79%	81%
Regular	1.8	1.99		
Special 1	5.86	4.54		
Special 2	5.03	5.54		
Special 3	9.76	9.51		
Special 4	8.18	9.28		
Gas			80%	83%
Regular	1.53	1.75		
Special 1	7.22	6.15		
Special 2	5.34	5.53		
Credit losses				
Credit risk	7.21	7.03		
Payment enforcement costs	5.97	6.03		
Service costs	2.32	2.32		

Table 2.3 shows the TDL of the validation samples (both cross-sectional (2007) and longitudinal (2008)). The TDL for both validation samples is rather stable, indicating that the parameter estimates are still valid after one year. The TDL ranges between 1.04 for retention to 9.76 for special electricity product 3. The relatively low TDL of retention (TDL

2007=1.04; TDL 2008=1.04), regular electricity (TDL 2007=1.80; TDL 2008=1.99), and regular gas (TDL 2007=1.53; TDL 2008=1.75) is acceptable, given the high actual occurrence of being retained and having these products. The credit risk model (TDL 2007=7.21; TDL 2008=7.03), the payment enforcement model (TDL 2007=5.97; TDL 2008=6.03) and the services costs model (TDL 2007=2.32; TDL 2008=2.32) perform well.

For the electricity and gas model (Equation 2.4) we computed, apart from TDL, also a hit rate. This hit rate is the percentage of customers for which the type of product was predicted correctly. Hit rates of 79% (2007) and 81% (2008) for the electricity model and 80% and 83% for the gas model, indicate that the product models give acceptable predictions.

2.4.3 Overall CV model

The overall predictive performance of our full model is assessed by comparing the predicted customer value to the real value of customers (RCV). The real customer value is computed separately for customers that are still present and customers that were not retained in the estimation year:

$$RCV\_retained_{it}=1=R\_Revenues_{it}*(1-R\_CreditRisk_{it})-R\_Payment\ EnforcementCosts_{it} -R\_ServiceCosts_{it} \tag{2.11}$$

where

- $R\_Revenues_i$ is the sum of electricity and gas revenues:

$$R\_Revenues_{it}=\sum_{j=1}^{J}[GC_j*SYU_{ji}*R\_Product_{jit}] \tag{2.12}$$

where

  - SYU_{ji} is the standard yearly electricity or gas usage, which indicates the expected amount of electricity or gas customer i will use in a year;
  - GC_j is the gross contribution per product;
  - $R\_Product_{jit}$ indicates the possession of product *j* by customer *i* at time t
- $R\_CreditRisk_{it}$ indicates the proportion of the revenues that will be cashed:

$$R\_Credit\ risk_{it}=R\_Collection_{it}*(1-0.85) \tag{2.13}$$

where

  - $R\_Collection_{it}$ indicates whether a customer *i* received a collection in period *t*. If this is the case, the credit risk will be corrected for the success of the collection agency and becomes 0.15 (1*(1-0.85)); if the customer does not receive a collection, the credit risk is 0.
- $R\_PaymnetEnforcementCosts_{it}$ represent the real payment enforcement costs:

$$R\_PaymentEnforcementCosts_{it}=R\_PaymentEnforcement_{it}*C_{PaymentEnforcement} \tag{2.14}$$

where

  - $R\_PaymentEnforcement_{it}$ equals 1 when a customer received more than one payment enforcement attempt (reminder, dunning, and/or collection) in the past year;
  - $C_{PaymentEnforcement}$ are the average costs per payment enforced customer.
- $R\_ServiceCosts_{it}$ are the service costs:

$$R\_ServiceCosts_{it}=R\_Service_{it}*C_{Service} \tag{2.15}$$

where

  - $R\_Service_{it}$ is 1 when customer *i* contacts the call center;
  - $C_{Service}$ are the average costs per contacting customer.

For customers that were not retained, we need to make an adjustment to the real value formula (Equation 2.11) that captures their value in the period they were still a customer at the firm. The only adjustment we need to make concerns the real revenues. Since we only have yearly energy usage, we cannot compute revenues based on actual energy usage in a fraction of a year. Therefore, we assume that defection is proportionally distributed over the months within a year, leading to an average retained period of 6 months. Hence, we assume that churned customers still yield 50% of their revenues. All costs, on the other hand can be measured in retrospect and should be included in a similar fashion as in the real value of retained customers. So for churned customers we get:

$$\begin{aligned} RCV\_churned_{it}=&R\_Revenues_{it}*0.5*(1-R\_CreditRisk_{it)}-R\_PaymentEnforcementCosts_{it}\\ &-R\_ServiceCosts_{it}\end{aligned} \tag{2.16}$$

The predicted and real CV are compared with the following metrics:
- the average deviation:

$$Average\ deviation(\%)=\frac{avg(CV_t)-avg(RCV_t)}{avg(CV_t)}*100\% \tag{2.17}$$

where:

– *avg(CV)* is the average predicted customer value over all customers (*I*):

$$avg(CV_t)=\frac{\sum_{i=1}^{I} CV_{it}}{I} \tag{2.18}$$

– *avg(RCV)* is the average real customer value over all customers (*I*):

$$avg(RCV_t)=\frac{\sum_{i=1}^{I} RCV_{it}}{I} \tag{2.19}$$

A smaller (absolute) average deviation indicates a better prediction of real customer value.

– the Pearson correlation between predicted and real value, which takes a value between 0 and 1, where 0 means that the predicted value is not at all correlated with the real value, and 1 means the prediction perfectly correlates with the real value.
– the MedAPE (Median Absolute Percentage Error, derived from MAPE, e.g. Leeflang et al. 2000, page 506):

$$MedAPE=Median\left(\frac{|RCV_{it}-CV_{it}|}{|RCV_{it}|}\right), \tag{2.20}$$

a lower MedAPE indicates a better predictive performance of the model.

– the Root Mean Squared Error (RMSE, e.g. Leeflang et al. 2000, page 506):

$$RMSE=\frac{\sum_{i=1}^{I}(RCV_{it}-CV_{it})^2}{I} \tag{2.21}$$

a lower RMSE indicates a better predictive performance of the model.

The first row in Table 2.4 shows the predictive performance of our complete CV model. Not only have we computed the above metrics for the whole customer base, but also for the best and the worst customer decile. These deciles are based on a ranking of all customers on their predicted CV. The 10% of customers with the highest predicted CV is called the "Best Decile"; the 10% of customers with the lowest predicted CV is the "Worst Decile".

Overall, our model's predictive performance is rather good. Both for the complete customer base (-7.5%) and the best decile (-2.8%) our average predicted CV is somewhat lower that the real CV, for the worst decile (14.4%) our predicted CV is higher than the real CV. The prediction over the total customer base has the highest correlation with the real CV (0.77), whereas the best decile has the lowest RMSE (32.78). All in all, our model performs best in the best decile, followed by the total customer base, and a little worse in the worst decile.

2.4.4 Examining the relevance of each CV component

In order to examine the relevance of each component to the complete CV model, we compare the complete model (Equation 2.1) to some simplified versions of this model, i.e. models consisting of one or only some of the components. To assess which of those models works best we compare them on the metrics that are introduced in section 2.4.3. The simplified models we use are the following:

B1. $CV_{LAGit} = CV_{it-1}$

B2. $CV_{RETit} = Retention_{it} * CV_{it-1}$

B3. $CV_{REVit} = Revenues_{it}$

B4. $CV_{REV\_RETit} = Retention_{it} * Revenues_{it}$

B5. $CV_{REV\_SERCSTit} = Revenues_{it} - ServiceCostsit$

B6. $CV_{REV\_PAYCSTit} = Revenues_{it} - PaymentEnforcementCosts_{it}$

B7. $C_{VREV\_CSTit} = Revenues_{it} - ServiceCosts_{it} - PaymentEnforcementCosts_{it}$

B8. $CV_{REV\_RET\_CSTit} = Retention_{it} * (Revenues_{it} - ServiceCosts_{it}) - PaymentEnforcementCosts_{it})$

B9. $CV_{REV\_RET\_CRKit} = Retention * Revenues_{it} * (1 - CreditRisk_{it}) * (1 - 0.85)$

B10. $C_{VREV\_PAYCST\_CRKit} = Revenues_{it} * (1 - CreditRiskit) * (1 - 0.85) - PaymentEnforcementCosts_{it}$

B11. $CV_{REV\_CST\_CRKit} = Revenues_{it} * (1 - CreditRiskit\ \ ) * (1 - 0.85) - ServiceCosts - PaymentEnforcementCosts_{it}$

Table 2.4: Predictive validity (% difference in averages, Pearson correlation, MedAPE, RMSE for overall best decile and worst decile).

Model	Overall				Best decile				Worst decile			
	%diff. in averages	Pearson corr.	MedAPE	RMSE	%diff. in averages	Pearson corr.	MedAPE	RMSE	%diff. in averages	Pearson corr.	MedAPE	RMSE
FullCVmodel	-7.5%	0.77	38.45	32.69	-2.8%	0.50	17.18	32.78	14.4%	0.35	52.83	46.55
B1.CV_{LAGit}	2.0%	0.70	0.00	38.86	13.2%	0.49	0.00	36.42	-45.5%	0.27	53.23	60.28
B2.CV_{RETit}	-3.5%	0.70	8.93	37.64	7.6%	0.50	6.10	33.62	-38.6%	0.27	54.15	56.42
B3.CV_{REVit}	36.8%	0.56	8.31	46.84	19.6%	0.38	6.89	50.69	152.1%	0.16	68.91	46.50
B4.CV_{REV_RETit}	31.9%	0.58	15.66	44.83	12.8%	0.40	12.26	45.34	169.8%	0.17	71.32	47.15
B5.$CV_{REV\_SERCSTit}$	22.3%	0.64	34.32	40.61	9.6%	0.42	11.71	41.11	669.9%	0.37	94.74	50.13
B6.$CV_{REV\_PAYCSTit}$	22.1%	0.76	17.22	34.83	10.1%	0.47	7.61	36.47	87.1%	0.36	75.35	50.65
B7.CV_{REV_CSTit}	-1.2%	0.77	34.90	32.59	3.3%	0.49	12.38	33.49	0.7%	0.35	50.30	46.42
B8.$CV_{REV\_RET\_CSTit}$	-6.9%	0.77	38.52	32.72	-2.8%	0.50	17.17	32.84	16.7%	0.35	53.73	46.65
B9.$CV_{REV\_RET\_CRKit}$	31.7%	0.58	15.83	44.57	12.2%	0.41	12.25	44.37	174.6%	0.17	71.56	47.57
B10.$CV_{REV\_PAYCST\_CRKit}$	21.8%	0.76	17.15	34.70	10.0%	0.47	7.63	36.34	81.3%	0.35	73.62	50.39
B11.$CV_{REV\_CST\_CRKit}$	-1.7%	0.77	34.86	32.57	3.2%	0.49	12.40	33.43	-1.2%	0.35	49.63	46.45

Table 2.4 (B1-B11) shows the results of the predictive performance of each of these models in comparison to real CV, again both for the total customer base and for the best and worst decile. Based on these metrics, the best model should include at least predicted revenues7, payment enforcement costs and service costs (B7). Depending on which metrics are deemed the most important, credit risk should be included as well (B11). Hence, 3 of the 4 components of our CV model are empirically proven to add to the CV prediction. Retention, unlike suggested by previous studies (e.g., Donkers, Verhoef, and De Jong 2007; Gupta, Lehman, and Stuart 2004) does not seem to substantially add to our one-year prediction of CV. However, it is likely that the effect of retention becomes more salient over time. Therefore, based on our empirical findings and the strong theoretical pledge for customer retention, we believe that a model containing all four considered components is the preferred model for a more than one year prediction of customer value.

2.5 USING THE CV MODEL FOR CHOOSING THE MOST SUITABLE ACTION

After predicting the CV components and computing total CV, we can simulate and examine the predicted value effect of several changed customer characteristics. We assume these changed characteristics could be caused by marketing actions. The marketing department of the focal company considers four possible actions to be conducted in the coming year:

1) Up-selling customers to Special Electricity Product 3, which has a higher gross contribution than any of the other electricity products. This up-sell may either include a change in electricity product (from any of the other electricity products to Special Electricity Product 3), or the addition of Special Electricity Product 3 to the product portfolio (which now consists of a gas contract only).
2) Making improvements to the website in such a way that fewer customers will contact the company.
3) Offering the possibility to choose the payment date, aiming at fewer customers for which payment enforcement attempts are needed.
4) Rewarding customers for their loyalty in order to increase customer retention by one year.

In addition, there is the option to do nothing. Some customers just do not seem to want anything (at least none of the four options specified here). Not approaching these customers may be more profitable than any of the four actions defined above. In the following sections we will describe how we can determine the most suitable action per customer, and how this can be used to compute the expected CV and profitability of each of the campaigns.

2.5.1 Determining the most suitable campaign per customer

In order to determine the most suitable campaign per customer, we should -for each customer- identify the campaign with the highest simulation value:

$$Most\ suitable\ action_{it}=max(\{Stimulation\ Value\ Action_{ait}:\wedge\ a\in\ A\wedge Simulation\ Value\ Action_{ait}>Cmarketing^{a}\}) \quad (2.22)$$

where

$$Simulation\ Value\ Action_{ait}=(CV_{ait}-CV_{it})*P(Success\ of\ Actiona_{it}=1) \quad (2.23)$$

where

- *Simulation Value Action*$_{ait}$ is the Simulation Value (SV) of action *a* for customer *i* for period *t*;
- CV_{ait} is the predicted CV at time *t* as a result of the simulation; to compute CV_{ait} we estimate the CV per customer in the same way as in Equation 2.1, but with changed relationship characteristics in the underlying formulas. For example, from Equation 2.2 we got $\alpha_c Relation_{cit}$, which actually is:

  $$\alpha_1 PaymentEnforcement_{t-1}, i+\alpha 2Service_{t-1,i}\_\alpha_3 RelationshipDuration_{it}+\sum_{n=4}^{N}\alpha_n Relation_{nit}$$

  In the original retention calculation for a customer *i* $PaymentEnforcement_{t-1}$ is 1; however, in the simulation for action 3 for this customer *i* for this equation we change $PaymentEnforcement_{t-1}$ is 1 to $PaymentEnforcement_{t-1}$ is 0; leaving all other characteristics unchanged. Changing this customer characteristic for customer *i* changes his predicted value for each component and consequently his total predicted CV;
- *P(Success of Action*$_{ait}$*=1)* is the likelihood of succeeding in action *a* for customer *i*, e.g. the likelihood that -because of action *a*- customer *i* does not have payment enforcement costs anymore. The average predicted success of an action is based on learnings from previous marketing campaigns and has been provided by the focal company. To determine the individual success probability for each action

a for each customer *i* this average is adjusted to the predicted probability on the respective CV component, e.g. the expected success of action 3 is 5%; the average $P(PaymentEnforcement_{it})$ is 12%; we assume that action 3 is more likely to succeed for customers with lower[8] $P(PaymentEnforcement_{it})$. So, in this example, the success probability of action 3 for customer *i* is:

$$P(Success\ of\ Action_{3it}=1)=\frac{0.05}{(1-0.12)}*[1-P(PaymmentEnforcement_{it}=1)]$$

- *A* is the set of actions, i.e. Action 1, 2, 3 and 4;
- $C_{marketing_a}$ are accompanying marketing costs for each action.

Table 2.5 shows the specification of the simulated changes in relationship characteristics, the average success probability $(P(Success\ of\ Action_{it}{}^{=1}))$, and the adjustment rule for individual success probability. Based on the inputs from Table 2.5 the simulation value (SV) for each customer for each action can be computed and the most suitable action for each customer can be chosen. To clarify the final step, we consider the following numerical (hypothetical) example. We assume there is a customer with payment enforcement costs in the previous year. Without any marketing action, this customer's expected CV this year is €5. If, however, this customer would not have had any payment costs at all in the previous year, his expected CV this year would be €25. So, if action 3 is successful the CV of this customer would go up by €20. This customer's payment enforcement probability was 34%, so his success probability for action 3 is $\frac{0.05}{(1-0.12)}*(1-0.34)=0.038$; consequently, the SV for this customer for action 3 is 20*0.038 is €0.76. If we furthermore assume (based on similar computations) that his SV for action 1 is €0.17; his SV for action 2 is €0.05; his SV for action 4 is €0.11, and the $C_{marketing_a}$ for each action is €0.20 we conclude that action 3 is the most suitable action for this customer. If, however, the SV for action 3 would only be €0.19 and the $C_{marketing_a}$ is unchanged, we would decide the most suitable action is to do nothing, since all simulated action values in that case would be lower than the marketing costs .

2.5.2 Overall CV consequences of simulated actions

After assigning each customer to his or her (single) most suitable action, the expected simulated value per action can be computed. Table 2.6 shows the percentage of customers, the relative change in CV, the average success probability, the percentage of total SV, the assumed total SV, assumed action costs and profitability for each action (with a SV higher than the costs of one mail pack).

Table 2.5: Simulation specification

Action	Simulated changes in relationship characteristics	Average succes probability	Adjustment rule for individual succes probability
1. Up-sell to special electricity product 3	*Producti,t-1=Special E Product 3* – If customer already has an electricity product, not being Special Product 3: • $Up\text{-}sell_{t-1}=1$ – If customer does not have an electricity product yet: • $Dual\ fuel_{t-1}=1$ • $SYU_{Electricity}=avg(SYU_{Electricity})$	4%	$\frac{0.04}{0.06}$ $*P(Product_{it}=Special\ E\ Product\ 3)$
2. Stimulate less customer contact	$Service_{i,t-1}=0$	2%	$\frac{0.02}{0.23}$ $*P(Service=1)$
3. Stimulate less payment enforcement	$Payment\ Enforcement_{i,t-1}=0$	5%	$\frac{0.05}{(1-0.12)}$ $*[1-P(PaymentEnforcement_{it}=1)]$
4. Increase customer retention by 1 year	$Relationship\ Duration_{i,t-1}+12\ (months)$	3%	$\frac{0.03}{0.92}$ $*P(Retention_{it}=1)$

From Table 2.6 we read that, based on the SV, 26% of the customers should receive an up-sell to special electricity product 3 action (action 1) and 12% should receive the action that stimulates less payment enforcement (action 3). Even though far more people should receive action 1, both the average increase in customer value per customer and the average success probability for action 3 are higher, which results in comparable total (share of) simulation value for these two actions. We furthermore see that if the costs per customer when executing action 1 are the same as the costs per customer when executing action 3, the total profitability of action 3 will be higher. However, this does not mean that action 3 should be executed on all 12% of the base in this group and action 1 should not be executed at all. Since Table 2.6 displays only average values and the computation of SV and profitability can be done per customer, it is very likely that the profitability of a customer within action 1 is higher than the profitability of another customer in action 3. In addition, the actual costs for action 1 and action 3 may differ. Hence, for budget allocation decisions based on SV the outcomes in Table 2.6 give a first direction for groups of customers, but looking at individual customers and actual estimated costs per action will yield the optimal result.

2.6 CONCLUSION

In marketing literature several CLV models can be found. Most include retention, revenues and direct marketing costs. In this study we contribute to the existing literature on CLV, with the inclusion of service costs and payment enforcement costs as value detractors and credit risk as revenue risk. This study assesses the importance of all these components with a one-year time frame (so actually we predict CV instead of CLV) and shows that a customer value model, at least in this industry, cannot do without the inclusion of credit losses and service costs. We believe that the inclusion of credit risk in our CV model is an important contribution. So far researchers assumed that all customers would pay their bills. Unfortunately, this is not true. In line with the findings of Schulze, Skiera, and Wiesel (2012), we show that specifically for some customers, credit risk is a very important value component. For retention, our results are at odds with previous studies (e.g., Donkers, Verhoef, and De Jong 2007; Gupta, Lehman, Stuart 2004), because this component does not seem to add much to our CV prediction.

A second contribution of this study is the demonstration of the way in which CV models can be used to make marketing decisions. We have provided an example of how firms can build a CV model and how they can use the outcomes of this model in marketing decision making. Of particular importance are the simulated value consequences of marketing actions. We simulate four different actions and show how a combination of changed CV due to the action and the success probability of that action lead to a simulation value per customer. This simulation value per customer can be used to identify the most suitable action for each customer. The proposed framework is a comprehensive framework, which can be applied in a broad variety of industries. So far researchers have developed very valuable approaches and models (e.g., Venkatesan and Kumar 2004), that are difficult to apply directly in a business context. Although our suggested approach is less sophisticated, it is very valuable in actual customer management. We applied this framework at the studied firm, which is now using the insights for developing effective strategies to improve CV. This definitely helps them to become more customer centric as they have adopted the CV metric in a comprehensive manner (Shah et al. 2006), and the expectations are that they will be able to grow the value of their customer base in the coming years using the applied approach.

Table 2.6: Simulation per action (in case of most suitable action per customer)

Action (a)	% of customers	% ΔCV_{it}* $\left(\frac{CV_{ait}-CV_{it}}{CV_{ait}}\right)$	Average succes probability	% of total SV	Total SV**	Action costs***	Profit
1. Up-sell to special electricity product 3	26%	101%	0.009	26%	€ 199k	€ 95k	€ 104k
2. Stimulate less customer contact	24%	194%	0.038	46%	€ 354k	€ 86k	€ 268k
3. Stimulate less payment enforcement	12%	1310%	0.032	26%	€ 196k	€ 44k	€ 152k
4. Increase customer retention by 1 year	3%	10%	0.029	2%	€ 15k	€ 10k	€ 5k
5. Do nothing	35%	0%	0.000	0%	€ 0	€ 0	€ 0

*both CV_{ait} and CV_{it} are always positive.

**assuming an average SV of €0.65 per customer and a base of 1.8 million customers (1.2 million receiving an action).

*** assuming average costs per customer per action of €0.20 and a base of 1.8 million customers.

2.7 MANAGERIAL IMPLICATIONS

In this study we built a customer value model for a Dutch energy supplier. This company now knows which components influence its customer profitability: revenues and retention are important, but credit losses and service costs are also relevant to include. This insight leads to a change in marketing strategy from selling as much as you can to any customer to targeting customers for specific actions based on their predicted CV; thereby also accounting for financial risks.

Our model facilitates marketing decision making by simulating the effect of several possible actions on customer characteristics and hence predicted customer value. For each customer a most suitable action can be defined, based on both the expected change in CV and the likelihood of success of the simulated action. In the past only the likelihood of success was used to determine which customers to include in a predefined action, not taking into account the effects of this action on the cost components of CV. With our model, the focal company will no longer execute marketing actions on customers with a high likelihood to respond, but a low expected change in CV. Instead, the company will focus on all aspects of profitability before deciding whether or not to target a customer for a specific action.

Not only does our model enable the possibility to pick the most suitable action per customer, but also does it provide guidelines on how to allocate marketing spending over different actions. All in all, with our CV model and the implications it has for marketing decision making, the focal company now has the possibility to increase the profitability of its customer base.

2.8 RESEARCH LIMITATIONS AND FUTURE RESEARCH

Certain limitations characterize this research, both for marketing academics and for the focal company. The main limitation from an academic point of view is the fact that we only had data for a two-year time period. If we would have had customer data over a longer time span, we could have validated the stability of our CLV model over time. Unfortunately, for now, the validation could only be from one year to the next. Future studies could include a longer time span to see if the CLV components keep relevance over time and to verify the stability of the individual models.

Furthermore, our model only considers value resulting from transactions with customers; future research could study value resulting from customer engagement, which is referred to as customer engagement value. The inclusion of these non-transactional characteristics may enrich our customer view and lead to more accurate predictions of customer value (Kumar et al. 2010).

Finally, for the focal company, the main challenge lies in lack of experience in designing successful actions, specifically for the service costs, credit losses, and retention components in our model. Our model provides a predicted simulation value indicating which customers to target for several actions, but does not tell the focal company exactly how to do so. Future studies could focus on this more qualitative aspect of the execution of marketing actions.

2.A APPENDIX

Table 2A.1: Parameter estimates relationship characteristics

		Parameter estim0es				
	Retention	Electricity products (ref= no electricity)				
Variable		Regular	Special 1	Special 2	Special 3	Special 4
Intercept	1.310**	-0.558**	-2.763**	-2.698**	-4.430**	-3.658**
PaymEnforcement t-1	-0.399**	-0.439**	-0.405**	-0.481**	-0.390**	-0.394**
Service t-1	-0.093**	-0.063**	-0.008**	-0.036**	-0.082**	-0.060**
Relationship duration	-0.001*	-0.004**	-0.005**	-0.006**	-0.006**	-0.004**
Electricity usage	-0.028**	-0.015**	-0.017**	-0.019**	-0.015**	-0.015**
Gas usage	0.000	-0.010**	-0.007**	-0.008**	-0.009**	-0.009**
Dual fuel	0.328**	1.963**	1.583**	1.916**	1.649**	1.614**
Electricty product (ref=regular)						
Special product 1	0.242**	-0.997**	6.103**	-0.056**	0.610**	0.613**
Special product 2	0.009	-0.870**	0.594**	6.781**	0.652**	0.599**
Special product 3	-0.086**	-1.255**	0.542	0.017	18.673**	0.413
Special product 4	-0.169**	-1.352**	0.194**	0.435**	0.346**	8.409**
Gas product (ref=regular)						
Special product 1	0.115**	-0.544**	-0.306**	-0.538**	-0.423**	-0.388**
Special product 2	-0.167**	-0.839**	-0.737**	-0.928**	-0.668**	-0.552**
Marketing effort t-1	0.024**	-0.012**	0.029**	0.004**	-0.061**	-0.010**
Upsell t-1	0.115**	0.084**	0.146**	0.054**	0.109**	0.078**
Cross-sell t-1	0.136**	-0.122**	-0.023**	0.001	-0.077**	-0.054**
Direct debit	-0.027*	-0.219**	-0.136**	-0.036**	-0.152**	-0.163**
Moving indicator t-1	-0.316**	-0.150**	-0.284**	-0.442**	-0.137**	-0.157**
Former monopolist	1.393**	1.708**	1.721**	1.733**	1.905**	1.781**

** significant at p <0.01; *significant at p <0.05

Table 2A.1: Parameter estimates relationship characteristics ctd.

	Parameter estimates					
	Gas products (ref= no gas)			Credit losses		Service costs
Variable	Regular	Special 1	Special 2	Credit risk	Payment enforcement	
Intercept	-3.397**	-5.240**	-4.029**	-3.084**	-0.335**	0.374**
PaymEnforcement t-1	-0.219**	-0.288**	-0.350**	2.481**	2.521**	0.303**
Service t-1	-0.068**	0.257**	-0.028*	0.520**	0.178**	1.102**
Relationship duration	0.005**	-0.005**	-0.001**	-0.013**	-0.012**	-0.006**
Electricity usage	-0.028**	-0.033**	-0.030**	-0.007**	-0.009**	0.001
Gas usage	0.015**	0.017**	0.014**	0.009**	0.007**	0.002*
Dual fuel	4.087**	3.196**	3.213**	0.074**	0.009	-0.029**
Electricty product (ref=regular)						
Special product 1	-0.674**	1.135**	-1.970**	-0.103**	-0.111**	0.166**
Special product 2	-0.643**	-0.855**	-1.037**	-0.001	-0.035	0.011
Special product 3	-0.581**	-1.009**	-1.215**	0.084**	0.013	0.080**
Special product 4	-0.712**	-1.321**	-0.402**	0.207	0.016	0.161**
Gas product (ref=regular)						
Special product 1	-6.142**	2.863**	-2.754**	0.106**	0.116**	-0.017
Special product 2	-4.954**	-0.434**	3.002**	0.094**	0.090**	0.122**
Marketing effort t-1	0.065**	0.257**	0.120**	-0.646**	-0.187**	-0.278**
Upsell t-1	-0.205**	0.286**	0.099**	-0.040	-0.038	0.061**
Cross-sell t-1	0.330**	0.443**	0.368**	0.173*	0.131*	0.110**
Direct debit	0.098**	0.203**	0.283**	-1.134**	-2.514**	-0.666**
Moving indicator t-1	-0.048**	-0.669**	-0.604**	-0.181**	0.033	-0.088**
Former monopolist	1.194**	1.065**	0.925**	-0.197**	-0.165**	-0.712 **

** significant at p <0.01; *significant at p <0.05

Table 2A.2: Parameter estimates socio deomgraphic variables

		Parameter estimates					
		Electricity products (ref= no electricity)					
Variable	**Retention**	**Regular**	**Special 1**	**Special 2**	**Special 3**	**Special 4**
Marital status (ref=single)						
Married	0.017	-0.016**	-0.006**	0.057**	-0.020**	-0.013**
Living together	-0.028	0.029**	0.014**	0.047**	0.042**	0.012**
Divorced	-0.078**	-0.096**	-0.086**	-0.061**	-0.098**	-0.096**
Number of children (ref= 4+)						
no children	0.081**	0.081**	0.075**	0.110**	0.075**	0.072**
1 child	0.060**	0.073**	0.051**	0.062**	0.063**	0.070**
2 children	0.070**	0.082**	0.051**	0.077**	0.067**	0.080**
3 children	0.086**	0.083**	0.059**	0.065**	0.072**	0.081**
Age head of household (ref = 65+)						
<= 24 yrs	-0.127**	-0.130**	-0.156**	-0.228**	-0.104**	-0.091**
25-34 yrs	-0.212**	-0.193**	-0.234**	-0.326**	-0.163**	-0.160**
35-44 yrs	-0.250**	-0.246**	-0.272**	-0.375**	-0.194**	-0.192**
45-54 yrs	-0.207**	-0.211**	-0.226**	-0.272**	-0.180**	-0.174**
55-64 yrs	-0.161**	-0.193**	-0.183**	-0.196**	-0.162**	-0.161**
Social class (ref= D)						
Class A	0.004	-0.038**	-0.048**	-0.036**	0.021**	-0.020**
Class B +	-0.005	-0.028**	-0.040**	-0.019**	0.000	-0.023**
Class B -	-0.044**	-0.084**	-0.074**	-0.047**	-0.081**	-0.084**
Class C	-0.015	-0.045**	-0.032**	-0.010**	-0.033**	-0.041**
Owns a car	0.030*	0.103**	0.082**	0.063**	0.091**	0.091**
Gives to charity	0.030**	0.043**	0.039**	0.008**	0.042**	0.039**
Buys on credit	-0.041*	-0.066**	-0.056**	-0.059**	-0.059**	-0.068**
Buys on internet	-0.082**	-0.102**	-0.081**	-0.053**	-0.083**	-0.098**

** significant at p <0.01; *significant at p <0.05

Table 2A.2: Parameter estimates socio deomgraphic variables ctd.

	Parameter estimates					
	Gas Products (ref= no gas)			Credit losses		Service costs
Variable	Regular	Special 1	Special 2	Credit risk	Payment enforcement	
Marital status (ref=single)						
Married	0.025*	0.038*	0.118**	-0.039*	-0.041**	0.031**
Living together	-0.104**	-0.092**	-0.064**	0.113**	0.087**	0.058**
Divorced	-0.008	-0.050	0.047*	0.034	0.082**	0.086**
Number of children (ref= 4+)						
no children	0.018	0.063	0.080**	-0.359**	-0.177**	-0.027
1 child	0.011	0.005	-0.007	-0.212**	-0.045	0.001
2 children	0.024	-0.037	0.011	-0.271**	-0.036	-0.026
3 children	0.069**	0.075	0.042	-0.227**	-0.063*	-0.041**
Age Head of household (ref = 65+)						
<= 24 yrs	0.076**	-0.175**	-0.106**	0.345**	0.336**	0.034**
25-34 yrs	0.057**	-0.243**	-0.198**	0.422**	0.396**	0.085**
35-44 yrs	0.057**	-0.220**	-0.214**	0.470**	0.464**	0.075**
45-54 yrs	0.016	-0.174**	-0.135**	0.396**	0.385**	0.034**
55-64 yrs	0.060**	-0.078**	0.000	0.253**	0.235**	0.034**
Social class (ref= D)						
Class A	0.028*	-0.141**	0.020	-0.191**	-0.020	-0.028**
Class B +	0.006	-0.098**	-0.007	-0.145**	-0.017	-0.009
Class B -	0.008	0.008	0.061**	-0.107**	0.013	0.007
Class C	0.019	0.021	0.053**	-0.022	0.016	0.021*
Owns a car	-0.063**	-0.034	-0.081**	-0.119**	-0.123**	-0.019*
Gives to charity	0.025**	0.068**	-0.012	-0.123**	-0.108**	-0.051**
Buys on credit	-0.027	-0.028	-0.030	0.141**	0.114**	0.052**
Buys on internet	-0.029**	-0.077**	0.023*	0.041**	0.035**	0.034**

** significant at p <0.01; *significant at p <0.05

Table 2A.3: Parameter estimates house related variables

		Parameter estimates				
		Electricity products (ref= no electricity)				
Variable	**Retention**	**Regular**	**Special 1**	**Special 2**	**Special 3**	**Special 4**
House type (ref= other)						
Villa	0.122	0.335**	0.301**	0.332**	0.291**	0.254**
Duplex	0.181*	0.273**	0.252**	0.328**	0.253**	0.222**
Corner house	0.211**	0.261**	0.210**	0.339**	0.260**	0.226**
Row house	0.206**	0.239**	0.184**	0.293**	0.243**	0.203**
Porch house	0.230**	0.251**	0.167**	0.265**	0.237**	0.232**
Flat	0.245**	0.280**	0.191**	0.263**	0.277**	0.265**
Farm house	0.129	0.304**	0.207**	0.287**	0.210**	0.201**
Elderly home	-0.273**	0.362**	0.173**	0.262**	0.304**	0.285**
House value (ref = € 500k +)						
N/A	-0.114**	0.081**	0.074**	0.030**	-0.027**	0.042**
Less then € 75k	-0.414**	-0.214**	-0.222**	-0.234**	-0.257**	-0.258**
€ 75k-150k	0.019	0.489**	0.449**	0.284**	0.346**	0.396**
€ 150k-250k	0.113**	0.337**	0.287**	0.186**	0.240**	0.288**
€ 250k-350k	0.084**	0.178**	0.160**	0.111**	0.128**	0.165**
€ 350k-500k	0.064**	0.026**	0.023**	0.014**	0.021**	0.035**
House surface (ref = 500 m^2 +)						
Less then 50 m^2	-0.163**	-0.113**	-0.127**	-0.178**	-0.087**	-0.113**
50-100 m^2	-0.080**	-0.221**	-0.189**	-0.196**	-0.169**	-0.185**
100-200 m^2	-0.085**	-0.183**	-0.147**	-0.233**	-0.145**	-0.149**
200-300 m^2	-0.075**	-0.198**	-0.150**	-0.247**	-0.167**	-0.153**
300-500 m^2	-0.021	-0.106**	-0.073**	-0.113**	-0.081**	-0.084**
House construction year (ref= 1996 +)						
Before 1915	-0.129**	-0.353**	-0.269**	-0.387**	-0.261**	-0.288**
1915-1945	-0.096**	-0.350**	-0.262**	-0.387**	-0.239**	-0.276**
1946-1975	-0.161**	-0.401**	-0.281**	-0.338**	-0.325**	-0.342**
1976-1990	-0.072**	-0.298**	-0.215**	-0.229**	-0.227**	-0.255**
1990-1995	0.014	-0.169**	-0.116**	-0.115**	-0.107**	-0.145**

** significant at p <0.01; *significant at p <0.05

Table 2A.3: Parameter estimates house related variables ctd.

	Parameter estimates					
	Gas products (ref= no gas)			Credit losses		Service costs
Variable	Regular	Special 1	Special 2	Credit risk	Payment enforcement	
House type (ref= other)						
Villa	0.008	0.052	0.198	-0.035	-0.174*	-0.073
Duplex	0.121	0.113	0.289**	-0.024	-0.123	-0.070
Corner house	0.068	-0.041	0.227*	0.049	-0.035	-0.062
Row house	0.076	-0.085	0.214*	0.113	-0.012	-0.030
Porch house	0.126	-0.192	0.212**	0.085	-0.041	-0.080
Flat	0.198**	-0.159	0.218*	0.022	-0.071	-0.098
Farm house	-0.062	-0.134	0.084	-0.089	-0.183	-0.116*
Elderly home	-0.828**	-1.181**	-0.620**	-0.360	-0.677**	-0.006
House value (ref = € 500k +)						
N/A	-0.255**	-0.005	-0.301**	0.444**	0.141**	0.014
Less then € 75k	-0.372**	0.073	-0.426**	0.330	0.250	0.533**
€ 75k-150k	-0.471**	-0.018	-0.654**	0.275**	0.030	-0.060**
€ 150k-250k	-0.191**	0.035	-0.394**	0.139**	-0.053	-0.126**
€ 250k-350k	-0.067**	0.141**	-0.180**	-0.026	-0.119**	-0.143**
€ 350k-500k	0.102**	0.203**	0.000	-0.068	-0.109**	-0.137**
House surface (ref = 500 m^2 +)						
Less then 50 m^2	0.062**	-0.038	-0.056*	-0.223**	-0.144**	-0.034*
50-100 m^2	0.330**	0.267**	0.279**	-0.175**	-0.099**	0.001
100-200 m^2	0.345**	0.329**	0.234**	-0.180**	-0.100**	-0.038**
200-300 m^2	0.338**	0.325**	0.231**	-0.189**	-0.096**	-0.039**
300-500 m^2	0.166**	0.182**	0.128**	-0.147**	-0.104**	-0.006
House construction year (ref= 1996 +)						
Before 1915	0.397**	0.355**	0.238**	0.279**	0.112**	-0.071**
1915-1945	0.476**	0.392**	0.324**	0.185**	0.076**	-0.062**
1946-1975	0.358**	0.385**	0.369**	0.245**	0.138**	-0.030**
1976-1990	0.304**	0.268**	0.318**	0.227**	0.101**	-0.063**
1990-1995	0.227**	0.201**	0.261**	0.125**	-0.018	-0.100**

** significant at p <0.01; *significant at p <0.05

Chapter 3

For new customers only: a study on the effect of acquisition campaigns on a service company's existing customers' CLV

3.1 INTRODUCTION

Consumers frequently encounter promotional deals. In some of these deals, discounts and expensive presents are offered; the only restriction to get those is to become a customer of the promoting company. These deals are nice if one is not a customer of the company yet, but for customers that already have an established relationship with a firm these deals may have a contrary effect and lead to dissatisfaction or negative word-of-mouth (e.g., Infonu.nl 2008; Novo 2005; O'Sullivan 2009).

Prior research in customer management has focused on the relation between new and existing customers as well. Two main streams of research can be identified: literature that focuses on the allocation of marketing resources (e.g., Blattberg and Deighton 1996); and literature that focuses on the effect of marketing strategies on the (future) value of new customers (e.g., Gupta et al. 2004; Gupta and Zeithaml 2006). A short overview of each stream will be discussed below.

Several studies have indentified the need for firms to balance their marketing expenditures between acquisition and retention in order to maximize customer equity (e.g., Berger and Nasr-Bechwati 2001; Blattberg and Deighton 1996; Farquhar 2005). In these studies, acquisition and retention activities are merely correlated by budget constraints. Reinartz and colleagues (2005) present a modeling framework for balancing resources between customer acquisition efforts and customer retention efforts, thereby simultaneously considering acquisition spending, retention spending, and customer profitability. In a framework that enables competing marketing strategy options to be traded off on the basis of projected financial return, Rust and colleagues (2004) operationalize the change in a firm's customer equity relative to the incremental expenditure necessary to produce the change. This approach considers the expected lifetime value of both existing customers and prospective customers, thereby incorporating acquisition and retention in the same model.

Another stream of research links retention to acquisition by examining the effect of specific acquisition strategies on future retention of the acquired customers (e.g. Thomas 2001). In order to boost short-term indicators of positive business performance firms sometimes use short term aggressive sales efforts (e.g., Farquhar 2005; Gupta and Lehmann 2003). Although these efforts may result in increased customer acquisition numbers, the quality of acquired customers is questionable (Anderson and Simester 2004; Villanueva, Yoo, and Hanssens 2008). Especially the use of price promotions to acquire new customers, results in switch-prone, disloyal customers (Anderson and Simester 2004; Farquhar and Panther 2008; Lewis 2006; Musalem and Joshi 2009; Peng and Wang 2006; Reibstein 2002). Apart from price, other effects of acquisition strategies, such as the effect of acquisition channels on future value have been studied as well (Bolton, Lemon, and Verhoef 2004; Keane and Wang 1996; Verhoef and Donkers 2005).

To summarize, acquisition and retention activities cannot be viewed as separate entities, but appear to be related. Prior studies have linked acquisition to retention either cross-sectionally, by distributing resources over these two stages in relationship marketing at one point in time; or with a longitudinal view, by examining the future value of prospective customers after these same customers have been acquired. Sirohi and colleagues (1998) find evidence to suggest tension in carrying out both retention and acquisition strategies, and pose a balance between these activities is needed so that efforts to acquire customers do not undermine retention. In addition, Schweidel and colleagues (2008) emphasize that models must be developed to determine what aspects of behavior are impacted by marketing activities. While some marketing activities may affect acquisition or retention rates (or both); they may also affect the relationship between the two processes. However, to the best of our knowledge no studies exist that examine the effect of acquisition campaigns on consumers that are current customers of the company that introduces the campaign. Even though acquisition campaigns are not aimed at existing customers, these customers may be aware of the existence of acquisition campaigns and their behavior may be influenced by this mere fact (Novo 2005). In this study we aim to fill in this research gap. The objectives of this article are threefold:

1. To investigate the effect of awareness of attractively priced acquisition campaigns on retention intention.
2. To identify other explanatory variables which affect the relationship between awareness and retention intention.
3. To calculate the Customer Lifetime Value (CLV) consequences of existing customers being aware of attractively priced acquisition campaigns.

We empirically test our model in the Dutch energy market in cooperation with one of the larger players in this industry. Investigating the possible effects of attractively priced acquisition campaigns on the CLV of existing customers will provide managers of the focal company with a comprehensive image of the total effects of acquisition propositions. In the assessment of acquisition campaigns, the effects on existing customers may easily be overlooked, possibly leading to an incorrect estimation of the success of the respective acquisition campaign. Knowing how the value of existing customers will be influenced by the introduction of acquisition campaigns allows managers to assess whether or not to launch the acquisition campaign and to take appropriate countermeasures if campaigns are introduced.

The remainder of this chapter is organized as follows. First, we will present our conceptual framework and theory. Then we test our framework with an application in the Dutch energy market. After examining the relationship between awareness and retention intentions, we quantify existing customers' CLV changes due to acquisition campaigns. A simulation will provide insight into the consequences of increased awareness or changed attractiveness.

3.2 CONCEPTUAL FRAMEWORK

This section describes a framework for examining the effect of the introduction of attractively priced acquisition campaigns on the CLV of existing customers. Our framework consists of two parts: in the first part we examine the effect of acquisition campaigns on existing customers' retention intention (block A in Figure 3.1); in the second part we assess the effect of changed retention intention on CLV (block B in Figure 3.1).

As can be seen in block A of Figure 3.1, we assert that in order to be influenced by a campaign, being aware of this campaign is a prerequisite. If existing customers are aware, it is expected that -after correcting for differences in customer characteristics- their awareness influences their intention to remain a customer at the focal company. In Section

3.2 hypotheses are developed on the relationship between awareness and retention. Apart from the direct effect of awareness on retention intention, we also expect to find effects of well-handled complaints and attractiveness of the offer. If customers' complaints about non-customers getting the offer are handled well, this may influence their intention to stay. Similarly, retention intention may be different for customers who think the campaign shows an attractive offer than for customers who find the offer unattractive. Section 3.2.2 describes these possible explanatory variables and their hypothesized effects.

Block B in Figure 3.1 shows that CLV is influenced by retention intention, customer characteristics (usage and product possession) and service recovery. Since in our case we assume that the company will compensate customers who take the effort of complaining by offering the acquisition proposition that caused the complaint, we expect a negative effect on the revenues (and consequently CLV) of the customers. Section 3.5 further discusses the described CLV consequences.

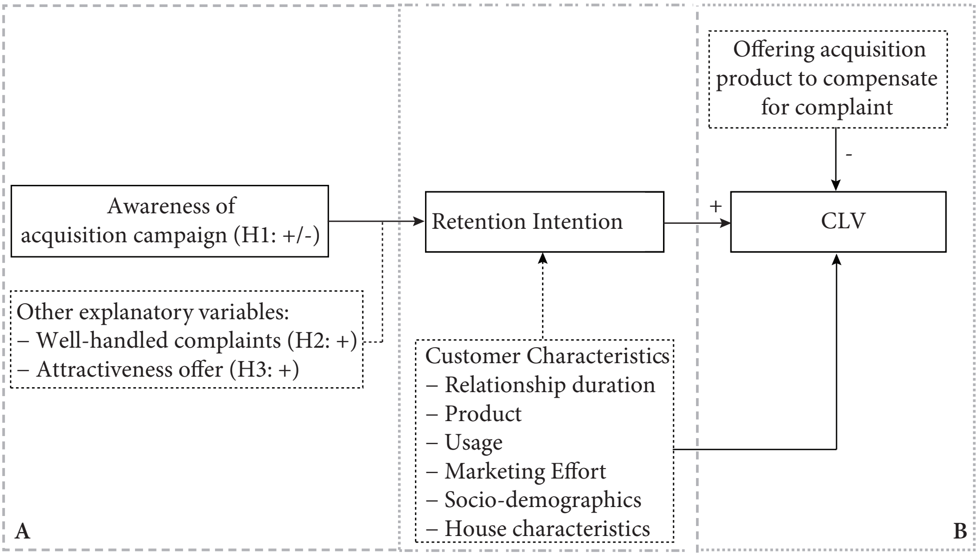


Figure 3.1: Conceptual framework

3.2.1 The influence of awareness on retention

Advertising is used to inform consumers about the existence, characteristics and economic value of a campaign; it creates awareness and knowledge among consumers, shapes their preferences and affects their behavior (Mehta, Chen, and Narasimhan 2008). Awareness refers to whether someone can recall or recognize a product or brand, or simply whether or not a consumer knows about a product or brand (Keller 2008, 2010). A certain extent of awareness appears to be a necessary condition for the effectiveness of campaigns. However, depending on situations as well as consumer characteristics, some consumers do not resort to counter-arguing and rather passively receive the advertising message (Vakratsas and Ambler 1999). Awareness of products, brands or campaigns, leads to the formation of attitudes or impressions at the time the information is received (Loken and Hoverstad 1985). Each reaction to advertising may or may not be linked to other information already existing in memory (Hunt and Einstein 1981; Keller 1987; Sar, Nan, and Myers 2010). For some people, exposure to campaigns may evoke feelings of familiarity (e.g., Aaker, Stayman, and Hagerty 1986), which in turn positively influences their preferences and reinforces their already formed attitudes (e.g., Batra and Ray 1986; Janiszewski and Warlop 1993; Mitchell and Olson 1981; Zajonc and Markus 1982). One might intuitively argue that advertising will have no effect on existing customers. However, in established relationships advertising might still play an important role by creating further brand preferences and positive brand associations (Vakratsas and Ambler 1999) that can strengthen the relationship over time. In the end, it is possible that the specific information that consumers can remember from ads fades (Rucker, Petty, and Priester 2007), but the meta-memories, or formed attitudes endure (Heath 2007). Even if customers have been exposed to and are aware of the acquisition campaigns, they may not be aware of the factual price difference between the product they have and the product being offered in the acquisition campaign. If the acquisition campaigns represent nice deals, regardless for which audience these deals are meant, the company may be associated with nice-deal-offering. Already being a customer at a company that offers nice deals, may reinforce the already positive attitudes and hence increase the intention to stay at the company. Therefore, advertising of acquisition campaigns could positively influence the customer's attitude, which should result in increased customer retention (e.g., Verhoef et al. 2009).

On the other hand, it is also possible that customers do remember the specifics of the acquisition campaigns, and are aware of the attractively priced deals (e.g., Lewis 2006) that are available to others for the same service or product (Feinberg, Krishna, and Zhang 2002; Maxwell 1999; Tsai and Lee 2007). Awareness of these price differences may evoke a feeling of being treated unfavorably, i.e. a feeling of perceived disadvantaged unfairness (Oliver and Swan 1989; Campbell 1999; Tsai and Lee 2007). Perceived unfairness may lead to negative emotions, such as disappointment, anger or even outrage (Xia, Monroe, and Cox 2004). Several of these emotions are associated with low customer satisfaction (Maute and Forrester 1993; Westbrook and Oliver 1991). When customers experience negative emotions or dissatisfaction, the most commonly encountered behavioral responses are: to complain, ask for a refund, spread negative word of mouth, leave the relationship, and/or not to take action and remain inert (Bougie, Pieters, and Zeelenberg 2003; Campbell 1999; Chen, Tsai, and Chuang 2010; Hirschman 1970; Singh 1988; Xia, Monroe, and Cox 2004; Zeelenberg and Pieters 2004; Zeithaml, Berry, and Parasuraman 1996). Much research attention has been devoted to investigating an array of moderating and mediating variables to better understand the behavioral responses of dissatisfied consumers (Nasr-Bechwati and Morrin 2003). It appears that the behavior that is most likely to occur depends on the severity of the accompanying emotion (e.g., dislike, anger or outrage; Díaz and Ruíz 2002; Roseman, Wiest, and Swartz 1994; Shaver et al. 1987); inferences about who caused the event that led to dissatisfaction; the extent of the firm's control of the situation that led to the dissatisfaction (Folkes, Koletsky, and Graham 1987; Maute and Forrester 1993); the customer's assessment of which action is most likely to restore fairness (Bougie, Pieters, and Zeelenberg 2003, Maute and Dubé 1999); and simple cost/benefit reasoning (Zeelenberg and Pieters 2004). So, it could be that awareness of acquisition campaigns leads to negative attitudes and decreased customer retention.

All in all, the existing marketing theory is not unambiguous in what relations to expect between awareness and retention intention. Therefore we formulate two opposing hypotheses:

Hypothesis 1: *Awareness of the attractively priced acquisition campaign positively influences retention intention.*

Hypothesis 2: *Awareness of the attractively priced acquisition campaign negatively influences retention intention.*

3.2.2 Possible other explanatory variables: complaining and attractiveness

Two factors that may possibly impact retention intention in case of awareness are complaining (in order to get the offer) and campaign attractiveness. Complaining refers to customer-initiated communications to the service provider (Bougie, Pieters, and Zeelenberg 2003), with the aim of being compensated for a disadvantaged situation (Chang and Hsiao 2008; Díaz and Ruíz 2002; Fornell and Wernerfelt 1988; Krishna, Dangayach, and Jain 2011; Orsingher, Valentini, and De Angelis 2010; Zeelenberg and Pieters 2004). Ample research has shown that effective complaint handling can have a dramatic impact on perceived justice, customer satisfaction, repurchase intentions, customer retention rates, decrease of negative word of mouth and third party complaining behavior (e.g., Fornell and

Wernerfelt 1987; Homburg and Fürst 2005; Pizzutti and Fernandes 2010; Smith, Bolton, and Wagner 1999; Soussa and Voss 2009; Tax, Brown, and Chandrashekaran 1998; Wang et al 2011; Zeithaml, Berry, and Parasuraman 1996). However, if the complaint handling is not effective and recovery fails, customers are very likely to switch providers (e.g., Álvarez, Casielles, and Martín 2010; Keaveney 1995; La and Choi 2012; Smith, Bolton, and Wagner 1999; Wirtz and McColl 2010). Complaint handling is considered to be effective when some form of compensation is offered (Blodgett, Granbois, and Walters 1993; Rothenberger, Grewal and Iyer 2008), preferably compensation in the form of resources that match the type and amount of loss the customer experienced (Chuang et al. 2012; Smith and Bolton 2002; Smith, Bolton, and Wagner 1999; Tax, Brown, and Chandreshekaran 1998; Vázquez, Iglesias, and Varela 2011). We assume that complaints are handled well and therefore we hypothesize:

Hypothesis 3: *Customers who complain have a higher retention intention than customers who do not complain.*

The role of attractiveness of the offer on retention intention has to the best of our knowledge not been studied in marketing literature. It could be the case that attractiveness-judgments of campaigns serve as simple cues to create overall company evaluations (Rucker, Petty, and Priester 2007). In case attractiveness is related to overall company evaluation, offers that are perceived to be unattractive, will create unfavorable attitudes towards the company, whereas attractive offers will lead to very favorable images, increased liking and consequently higher likelihoods of staying at the company. On the other hand, it is also imaginable that highly attractive offers lead to higher perceptions of unfairness and result in decreased retention intention (Tsai and Lee 2007). Therefore we formulate two opposing hypotheses:

Hypothesis 4: *The more attractive the offer is perceived to be, the higher the retention intention.*

Hypothesis 5: *The more attractive the offer is perceived to be, the lower the retention intention.*

3.3 EMPIRICAL APPLICATION

3.3.1 Data description

We use three data sources: survey data, customer behavioral data from the focal company in the Dutch energy market, and external consumer data. These three data sources are merged to construct a final database of 1871 customers. The variables of interest: awareness, retention intention, complaining intention and attractiveness appear in the survey (see section 3.3.1.1). The customer behavioral data and external consumer data are used to explain the differences found in the dependent variable (the customer characteristics in Figure 3.1).

3.3.1.1 Sample and survey design

The sample for the study was composed of a random selection of 60k customers of the focal company that opted-in for receiving email. The selected customers received an e-mail with a link to an online survey, which obtained a response rate of 5.4 percent; yielding surveys from 3298 customers. The survey contains five different sections[9]: a section measuring retention intention, a section to quantify (aided) awareness, a section to measure the attractiveness of the acquisition campaign, a section to investigate complaint intentions and past complaint behavior, and a section with background questions. In order to be able to test our conceptual model, it is essential to have the answer to the retention intention questions. So, we excluded all respondents not having filled out these questions. In addition, we excluded all respondents that have not finished the survey and those that could not be matched to the database of the focal company. In total this yielded a dataset of 1871 representative[10] respondents who were all existing customers of the focal company at the time of sending out the survey.

3.3.1.2 Measures, constructs and instruments

Retention intention: The survey contains two retention questions, each measuring a different time scope and posed in a slightly different manner: 1) Do you intend to look around at the energy market in the coming 3 months? 2) Do you think you will still be a customer in 12 months? Two time scopes are used, because retention intentions in the short term may differ from the same customer's retention intentions in the longer term. In order to avoid confusion, the questions are posed with reversed scales. Both questions are measured using a slider (a bar below the question on which respondents can place the slider by clicking on any desired position on the bar) representing a value between 0 and 100 percent. Sliders are often used in medical applications (e.g., Pijncentrum Rijnstate Ziekenhuis 2011; Ziekenhuis de Tjongerschans 2009) to indicate pain intensity. People have difficulties in indicating how likely it is that they will engage in certain behaviors, sliders have shown to facilitate the requested judgments (e.g., De Rond et al. 2000). Since the 3 month and 12 month retention intention are highly correlated (Cronbach's Alpha= 0.82; Pearson Correlation=0.70) we have decided to combine these scales into one single (average) measure. Interestingly, customers' average retention intention (75%) is much lower than the actual retention (91%).

Aided awareness: Aided awareness is adopted from studies by Quester (1997) and Huang and Sarigöllü (2012) and measured by asking respondents: "Are you familiar with campaign X?" For campaign X we chose six different campaigns, three recent campaigns of the focal company and 3 campaigns of 3 other energy suppliers. The competitive offers are included because of the assertion that competition is an important driver of customer behavior (Polo, Sese, and Verhoef 2011), and customer retention in particular (Shum 2004). Both the name and a short description of each campaign are given.

Attractiveness: If customers are aware of any of the three focal company's campaigns, three questions are asked in order to evaluate the attractiveness of the respective campaign. Two attractiveness questions ("the offer is attractive" and "the offer is rewarding") are adopted from Grewal et al. (1998); the third statement measures fairness of the campaign ("the offer is fair") and is based on items used by Campbell (1999) and Tsai and Lee (2007). All three statements consist of a 7-point scale ranging from definitely not to definitely so (Crano and Brewer 2002). The Cronbach's Alpha (0.89) shows that the items used to measure campaign attractiveness result in a reliable scale. Hence, the three items are averaged to form a measure for campaign attractiveness. Attractiveness in turn is split into three groups: low (score<3.66), average (3.66<=score<=4.33) and high (score>4.33) attractiveness. Since attractiveness of the focal acquisition campaign is only known for aware customers, and the exclusion of unaware customers from the analysis is not an option, three attractiveness dummies have been created for aware customers: in low (5%), average (9%) and high (6%) attractiveness rating. The group of customers that is unaware of the acquisition campaigns of the focal company (80%) is used as a reference category.

Complaint behavior: The purpose of the complaint questions is to identify whether aware customers contacted the focal company. Respondents are asked whether they have already switched to the contract offered in the campaign (adopted from Rothenberger, Grewal, and Iyer 2008) or contacted the focal company to get the offer.

Background: This section contains a set of multiple choice questions regarding the respondent's credentials and asks for the customer's address. These questions are used to test for randomness of the sample and to enable a linkage to the focal company's database.

3.3.1.3 Customer behavioral and external consumer data

The customer behavioral data stems from the focal energy supplier's database, and includes historical and recent characteristics like service costs, payment enforcement issues, relationship duration, energy usage, product possession, payment method, and information on the region the customer lives in. External consumer data are bought from Acxiom, and include socio-demographic characteristics, lifestyle information and information on the house the consumer lives in. All this information is provided at the individual household level (based on actual and estimated data) and can be linked to the survey sample. The inclusion of all these variables as predictors of retention intention increases the likelihood that heterogeneity between customers is accounted for (Leeflang and Wittink 2000).

3.3.2 Resulting dataset

All described data have been combined into one dataset of which Table 3.1 contains the most important descriptive statistics. It is noteworthy that 20% of the customers are aware of the focal company's acquisition campaigns, whereas 67% of the customers are aware of the acquisition campaigns of the focal company's competitors. This large difference in awareness is mainly due to the campaigns of one competitor which only advertises with "lower prices"; a statement that is much easier to remember then the more concrete advertising by the focal company and the other competitors. Of the customers that are aware of the focal company's campaign, 15% bothered to contact the company (to complain).

3.3.3 Retention intention model

Retention intention is expressed as a percentage, i.e. contains only values between 0 and 100. In order to make valid predictions of this variable, a logit transformation[11] has been applied. For the basic model, that is a model investigating the effect of awareness on retention, a simple linear regression model is estimated:

$$Logit\_Retention_i = \beta_0 + \beta_1 Aware_i + \sum_{k=1}^{K} \gamma_k X_{ki} + \varepsilon_i \tag{3.1}$$

where

- $Logit\_Retention_i$ is the logit transformation of retention intention for customer *i*;
- $Aware_i$ is a dummy for customer *i's* awareness (0=unaware; 1=aware);
- X_{ki} are various covariates (e.g. relationship duration, product usage) for customer *i*.

In order to test the effect of well-handled complaints and attractiveness of the offer, the simple model is adapted with several combinations of variables:

$$Logit\_Retention_i = \beta_0 + \beta_1 Aware_i + \beta_2 Complain_i + \sum_{k=1}^{K} \gamma_k X_{ki} + \varepsilon_i \tag{3.2}$$

$$Logit\_Retention_i = \beta_0 + \beta_1 AwareHiattract_i + \beta_2 AwareLoattract_i + \beta_3 AwareAvgattract_i + \sum_{k=1}^{K} \gamma_k X_{ki} + \varepsilon_i \tag{3.3}$$

$$Logit\_Retention_i = \beta_0 + \beta_1 AwareHiattract_i + \beta_2 AwareLoattract_i + \beta_3 AwareAvgattract_i + \beta_4 Complain_i \sum_{k=1}^{K} \gamma_k X_{ki} + \varepsilon_i \tag{3.4}$$

where

- $Complain_i$ is a dummy indicating whether customer i has complained (and got the acquisition offer);
- $AwareHiAttract_i$ is a dummy indicating that customer i is aware and rates the campaign as very attractive;
- $AwareLoAttract_i$ is a dummy indicating that customer i is aware and rates the campaign as unattractive;
- $AwareAvgiAttract_i$ is a dummy indicating that customer i is aware and rates the campaign as averagely attractive.

Table 3.1: Descriptive statistics

Variable	Mean	Std dev	Minimum	Maximum
Average retention intention	72	26	0	100
Relationship duration (mnths)	96	37	5	123
Gas usage	1430	1086	0	9739

Variable	% dataset
Actual retention	91%
Dummy aware	20%
Dummy aware and complaining	3%
Dummy aware and low attractiveness	5%
Dummy aware and average attractiveness	9%
Dummy aware and high attractiveness	6%
Dummy aware of competitor's campaign	67%
Survey version 1	19%
Survey version 2	18%
Survey version 3	19%
Survey version 4	38%
Survey version 5	3%
Survey version 6	3%
Dummy fixed price product (E/G)	48%
Dummy inbound contact past year	32%
Dummy electricity area	86%

3.4 RESULTS

3.4.1 Awareness and retention, simple model

Table 3.2 gives the results of the estimation of all four retention intention models. From the columns under Model 1 it can be read that awareness is positively related to retention intention (β=0.243; $p < 0.05$), when taking into account several (significant) covariates (customer characteristics). This means that customers who are aware, are more inclined to stay at the focal company, hence Hypothesis 1 is supported whereas Hypothesis 2 is rejected. In addition, some customer characteristics influence the retention intention. Noteworthy is the effect of awareness of competitive offers. Customers who have indicated to be aware of competitive offers are more inclined to leave the company (β=-0.649; $p < 0.01$). The positive effect of awareness of the focal company's acquisition campaigns is not large enough to offset the negative effect of the competitive campaigns (t=2.711). Other effects that are worth mentioning are the negative influence of survey version 2 (β=-0.357; p=0.0042) and the positive influence of survey version 3 (β=0.327; $p < 0.01$) on retention intention. In version 2 customers were first asked about their satisfaction with the focal company and then they were asked to indicate their retention intention. Being asked about satisfaction appears to negatively influence retention intention. In survey version 3, respondents were first asked about awareness and then about their intention to stay at the focal company. Apparently, being reminded of campaigns increases the inclination to stay.

3.4.2 Adding the other explanatory variables

In order to gain deeper understanding of the relationship between awareness and retention intention, the variables "well-handled complaint" and "attractiveness" have been added to our simple model. The covariates have been kept constant, i.e. the simple models have only been extended by the inclusion of (combinations of) these explanatory variables. Model 2 to 4 in Table 3.2 give a summary of the results of the model extensions, still with the logit of retention intention as a dependent variable. The inclusion of the complaint dummy (Model 2 and Model 4) does not lead to a better model (see Table 3.2): the presence of a well-handled complaint does not significantly influence retention intention; it even makes the effect of awareness on retention intention insignificant. So, Hypothesis 3 is rejected. The inclusion of the attractiveness dummies (Model 3 and 4) leads to more promising results: the model fit increases, i.e. the adjusted R-squared goes from 0.095 to 0.104[12]; the AIC drops from 2641 to 2624 and the Schwartz criterion goes from 2725 to 2718.

Table 3.2: Estimation results of (logit transformation of) retention intention

Variable	Model 1			Model 2			Model 3			Model 4		
	Parameter estimate (standardized)		t value	Parameter estimate (standardized)		t value	Parameter estimate (standardized)		t value	Parameter estimate (standardized)		t value
Intercept	1.395		7.11**	1.401		7.14**	1.392		7.13**	1.393		7.13**
Dummy aware	0.243	(0.046)	2.08*	0.194	(0.037)	1.6						
Dummy complain				0.401	(0.032)	1.4				0.069	(0.006)	-1.99*
Dummy aware + low attractiveness							-0.429	(-0.044)	-1.98*	-0.432	(-0.044)	1.47
Dummy aware + avg attractiveness							0.245	(0.033)	1.5	0.241	(0.033)	3.89**
Dummy aware + high attractiveness							0.855	(0.096)	4.35**	0.835	(0.094)	0.23
Dummy aware of competitive offer	-0.649	(-0.144)	-6.50**	-0.641	(-0.143)	-6.41**	-0.651	(-0.145)	-6.56**	-0.650	(-0.144)	-6.53**
Survey version 2	-0.357	(-0.065)	-2.86**	-0.357	(-0.065)	-2.86**	-0.347	(-0.063)	-2.8**	-0.347	(-0.063)	-2.79**
Survey version 3	0.327	(0.060)	2.65**	0.331	(0.061)	2.68**	0.341	(0.063)	2.78**	0.341	(0.063)	2.78**
Gas usage	0.000	(-0.080)	-3.45**	0.000	(-0.081)	-3.46**	0.000	(-0.081)	-3.48**	0.000	(-0.081)	-3.48**
Dummy fixed price product (E/G)	0.531	(0.125)	5.58**	0.529	(0.125)	5.57**	0.499	(0.118)	5.26**	0.500	(0.118)	5.26**
Dummy inbound contact past year	-0.312	(-0.068)	-3.00**	-0.326	(-0.071)	-3.12**	-0.310	(-0.068)	-3.00**	-0.313	(-0.069)	-3.01**
Dummy Alliander electricity	0.461	(0.075)	2.60**	0.457	(0.075)	2.59**	0.472	(0.077)	2.68**	0.471	(0.077)	2.68**
Relationship duration (mnths)	0.005	(0.095)	3.27**	0.005	(0.094)	3.25**	0.005	(0.095)	3.29**	0.005	(0.094)	3.28**
Dummy age 35-44 years	0.270	(0.046)	2.08*	0.266	(0.046)	2.05*	0.287	(0.049)	2.22*	0.286	(0.049)	2.21*
Dummy number children>=4	-0.639	(-0.058)	-2.63**	-0.645	(-0.059)	-2.66**	-0.673	(-0.061)	-2.78**	-0.674	(-0.062)	-2.79**
Dummy construction house 1931-1945	-0.505	(-0.055)	-2.47*	-0.497	(-0.054)	-2.43*	-0.520	(-0.056)	-2.56*	-0.518	(-0.056)	-2.55*
Dummy construction house 2001-2005	-0.509	(-0.057)	-2.52*	-0.513	(-0.057)	-2.53*	-0.508	(-0.057)	-2.52*	-0.509	(-0.057)	-2.52*
Dummy owner-occupied house	-0.251	(-0.057)	-2.46*	-0.254	(-0.057)	-2.48*	-0.247	(-0.056)	-2.43*	-0.248	(-0.056)	-2.44*
Model fit												
Adj R-squared	0.0951			0.0949			0.1044			0.1040		
AIC	2641			2643			2624			2626		
Schwartz BIC	2725			2731			2718			2726		

* significant at p<0.01; *significant at p<0.05

Overall, looking at the measures of model fit, retention intention is fitted best by the model including not only awareness but also an indication of attractiveness of the campaign of which the customer is aware (Model 3). In this model we find a negative effect (β=-0.429; $p < .0.05$) of unattractive acquisition campaigns on retention intention; moderate evaluations of attractiveness do not significantly influence the retention intention ($p > 0.10$); and if customers evaluate the campaign as being highly attractive, a significantly higher retention intention (β=0.855; $p < 0.01$) is found. So, compared to unaware customers, aware customers that positively evaluate the attractiveness of the focal company's acquisition campaigns tend to be more inclined to stay for another year, whereas customers who find the focal company's campaign unattractive tend to be less inclined to stay. The positive effect, however, is larger than the negative effect (t=1.51). Hence, the results with respect to attractiveness support Hypothesis 4.

3.4.3 Checking for reverse causality

Now that we know that both awareness and attractiveness are positively related to retention intention, we should check whether there is an endogeneity issue, i.e. whether attractiveness is actually causing retention intention or is caused by it. If this would be the case, it may be that customers rate an offer as attractive, simply because they indicated they have a high intention to stay, which would make the found effects of rather limited use. In order to test for endogeneity we performed two Hausman tests (e.g., Verbeek 2000), one for awareness and one for attractiveness. First, we made awareness exogenous by predicting awareness (with a binary logistic regression) from only exogenous variables. Then we included the residuals[13] in the retention equation (Equation 3.1), in order to test the null-hypothesis that there is no simultaneity (Greene 2000). As can be seen from Table 3.3, the residual variable (in the model with residual) is not significantly related to the logit of retention intention ($p>0.10$), hence the null-hypothesis is not rejected. So, we can conclude that awareness is not caused by retention intention, i.e. customers do not indicate to be aware because they have indicated they have a high retention intention. For attractiveness, we ran a similar analysis, but only for aware customers (since the attractiveness information is lacking for unaware customers). The inclusion of aware customers only changes the variables to be included in the (logit of) retention intention equation, as can be seen in the model without residual in Table 3.4. This model with residual in Table 3.4 shows that the residual of attractiveness is not significantly related to retention intention ($p > 0.10$), consequently also for attractiveness the null-hypothesis of no simultaneity is not rejected. This leads to the conclusion that customers do not rate the campaign as more attractive merely because they indicated to have a high intention to stay. Ergo, the results established in section 3.4.1 and 3.4.2 are not biased by endogeneity issues.

Table 3.3: Hausman test for awareness and (logit transformation of) retention intention

Variable	Without residual: Parameter estimate (standardized)	Without residual: t value	With residual: Parameter estimate (standardized)	With residual: t value
Residual predicted awareness			-0.325 (-0.153)	-1.56
Intercept	1.395 (0.000)	7.11**	1.230 (0.000)	5.52**
Dummy aware	0.243 (0.046)	2.08*	1.026 (0.195)	1.99*
Dummy aware of competitive offer	-0.649 (-0.144)	-6.5**	-0.643 (-0.143)	-6.44**
Survey version 2	-0.357 (-0.065)	-2.86**	-0.357 (-0.065)	-2.86**
Survey version 3	0.327 (0.060)	2.65**	0.336 (0.062)	2.72**
Gas usage	0.000 (-0.080)	-3.45**	0.000 (-0.078)	-3.32**
Dummy fixed price product (E/G)	0.531 (0.125)	5.58**	0.535 (0.126)	5.62**
Dummy inbound contact past year	-0.312 (-0.068)	-3**	-0.355 (-0.078)	-3.3**
Dummy Alliander electricity	0.461 (0.075)	2.6**	0.454 (0.074)	2.57*
Relationship duration (mnths)	0.005 (0.095)	3.27**	0.005 (0.094)	3.26**
Dummy age 35-44 years	0.270 (0.046)	2.08*	0.269 (0.046)	2.07*
Dummy number children>=4	-0.639 (-0.058)	-2.63**	-0.647 (-0.059)	-2.67**
Dummy construction house 1931-1945	-0.505 (-0.055)	-2.47*	-0.495 (-0.054)	-2.42*
Dummy construction house 2001-2005	-0.509 (-0.057)	-2.52*	-0.485 (-0.054)	-2.39*
Dummy owner-occupied house	-0.251 (-0.057)	-2.46*	-0.237 (-0.054)	-2.31*

*significant at $p < 0.01$; *significant at $p < 0.05$

Table 3.4: Hausman test for attractiveness and (logit transformation of) retention intention

Variable	Without residual: Parameter estimate (standardized)	Without residual: t value	With residual: Parameter estimate (standardized)	With residual: t value
Residual predicted awareness			0.161 (0.092)	0.59
Intercept	-0.759 (0.000)	-1.58	-0.209 (0.000)	-0.2
Attractiveness	0.468 (0.280)	6.06**	0.322 (0.193)	1.24
Relationship duration (mnths)	0.011 (0.199)	4.26**	0.011 (0.199)	4.27**
Dummy age 45-54 years	-1.201 (-0.225)	-4.48**	-1.174 (-0.219)	-4.32**
Dummy age youngest child 13-17 yrs	1.544 (0.178)	3.69**	1.557 (0.179)	3.71**
Dummy social class D	0.913 (0.120)	2.54*	0.904 (0.119)	2.51*
Dummy working Sector: business	0.895 (0.1990)	4.06**	0.898 (0.200)	4.07**
Dummy lives in a farm house	-1.555 (-0.1080)	-2.32*	-1.564 (-0.108)	-2.33*
Dummy own car	-0.694 -0.121	-2.59*	-0.682 -0.119	-2.54*

*significant at $p < 0.01$; *significant at $p < 0.05$

3.5 CALCULATING CLV CONSEQUENCES

3.5.1 Computing customer lifetime value (CLV)

CLV is defined as the discounted value of all expected future customer profits in a determined time period (Bolton, Lemon and, Verhoef 2004). The CLV of a customer for a company is computed as profit (revenues minus service costs) of a customer *i* in a certain time period *t*, divided by a discount rate *d*, for each expected time period the customer's relationship with the firm is retained[14] (Berger and Nasr 1998; Reinartz and Kumar 2000):

$$CLV_i = \sum_{t=0}^{T} \frac{Retention_{it} + *(Revenues_{it} - ServiceCosts_{it})}{(1+d)^t} - SalesCosts_i \tag{3.5}$$

The retention component, as we have established, is influenced by the introduction of an acquisition campaign. Because respondents may find it difficult to indicate a retention intention that differs over time, we assume that there is only one retention rate per customer (a persistent retention effect) turning $Retention_{it}$ into $Retention_i$. The retention rate is scaled slightly to resemble actual retention rates[15], because consumers overestimate their intention to leave the company. The focal company has the policy of offering the respective acquisition propositions to complaining customers, so the revenues and sales costs (i.e. costs for actually making the offer by a sales agent) of these complaining customers will be affected by the acquisition campaign as well. Since customers are only likely to complain when their contract is more expensive than the acquisition contract, offering the acquisition contract, ceteris paribus, results in lower revenues. We allocate the sales costs only once to those customers that complain (in the year in which the product is changed into the acquisition product) and keep the amount fixed, regardless of the channel that was used to complain. Customers that do not complain will have no sales costs. If customers do not complain, the yearly revenues are computed as follows:

$$Revenues_{non\text{-}complainers_{it}} = \sum_{j=1}^{J} [SYU_{product_{ij}} * GC_{product_j}] \tag{3.6}$$

where

- $SYU_{product_{ij}}$ is the standard yearly energy usage for customer *i*, for product *j* (often one electricity product and one gas product);
- $GC_{product_j}$ is the gross contribution or margin of product *j*.

If, however, the customer does complain, the gross contribution will be set to a low (constant) amount corresponding to the average acquisition campaign. Since the average acquisition proposition involves a 3-year contract, the lower gross contribution will be allocated for 3 years, after that the gross contribution will be adjusted and set to the amount of a regular discount product. So, for complaining customers we get:

$$Revenues_{non\text{-}complainers_{it}} = \sum_{j=1}^{J} [SYU_{product_{ij}} * GC_{product_{jt}}] \tag{3.7}$$

where $GC_{product_{jt}}$ is the gross contribution which is constant in the first 3 years and changes once afterwards. The service costs are the same for all customers, and are based on average payment enforcement costs and contact costs. All the above simplifies the CLV equation to:

$$CLV_i = \sum_{t=0}^{T} \frac{Retention_i^t + *(Revenues_{it} - ServiceCosts_{it})}{(1+d)^t} - SalesCosts_i \tag{3.8}$$

where

- $Revenues_{it}$ depends on whether or not the customer complains (see equation 3.6 and 3.7)
- $SalesCosts_i$ are 0 in case customers do not complain.

3.5.2 Examining the CLV consequences per awareness and attractiveness group

Equation 3.8 has been computed for all customers, with lifetimes varying from 1 to 5 years. The resulting average CLV consequences of the introduction of an acquisition campaign are then examined. A comparison of CLV between aware and unaware customers[16] is shown in Figure 3.2a; Figure 3.3a compares unaware customers to aware customers with low, average or high attractiveness ratings.

As can be seen in figure 3.2a, the differences between CLV of unaware and aware customers in case an acquisition campaign is introduced are negligible small. A One-way-ANOVA shows that these differences are not-significant (F-value between 0.000 and 0.796). However, a comparison of the retention intentions of aware versus unaware customer is significant, in the advantage of aware customers (Figure 3.2b; F-value between 4.591 and 7.532). This implies that the higher retention intention is annulled by lower revenues and higher cost to sell due to complaining customers.

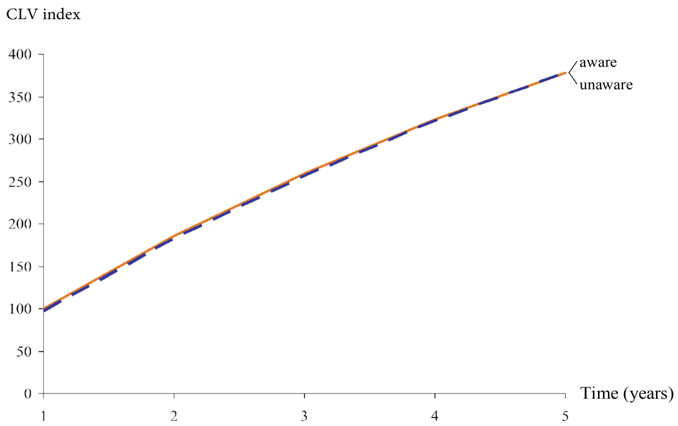


Figure 3.2a: Average CLV unaware vs. aware

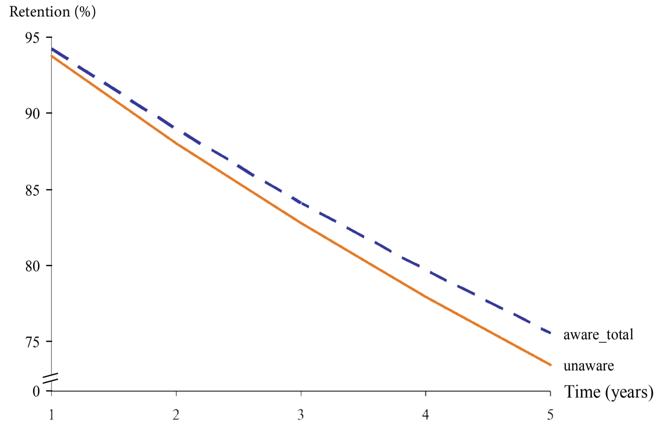


Figure 3.2b: Average predicted retention unaware vs. aware

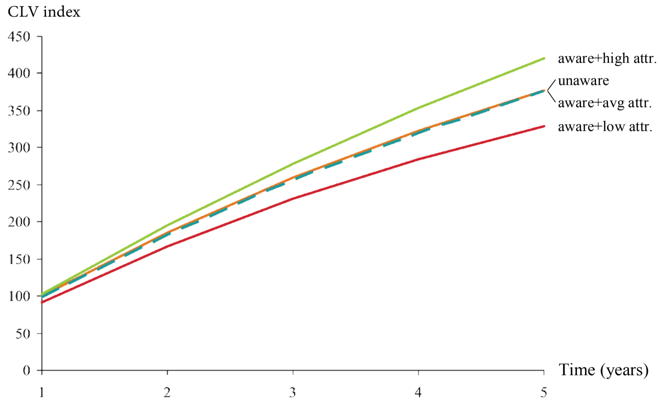


Figure 3.3a: Average CLV unaware vs. aware (per attractiveness segment)

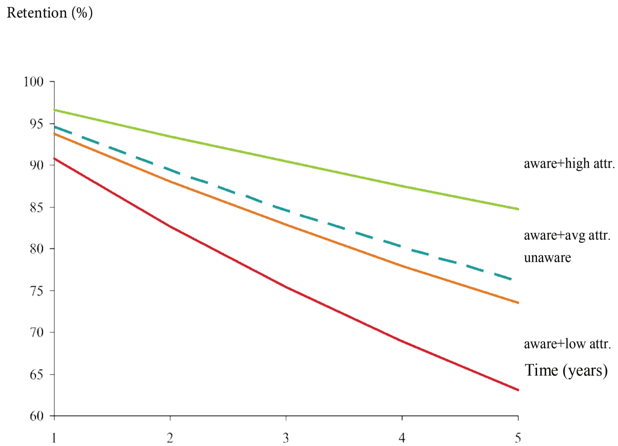


Figure 3.3b: Average predicted retention unaware vs. aware (per attractiveness segment)

Figure 3.3a shows the CLV comparison between unaware and the three attractiveness segments of aware customers. The CLV differences between "unaware" and "aware, with average attractiveness ratings" in case of the introduction of an acquisition campaign is insignificant (F-value between 0.021 and 0.416 across the 5 years), even though the retention intention difference is significant (Figure 3.3b; F-value between 5.850 and 6.278). So, here also, the higher retention intention is canceled by lower revenues and higher cost to sell due to complaining customers. "Aware, low attractiveness" customers have a significantly lower CLV than unaware customers from the fourth year onwards (F-value between 4.070 and 4.758). Since the percentage of complaining customers is relatively low in the low attractiveness group (5.7%, as compared to 29.3% in the high attractiveness group), the revenue consequences of the introduction of an acquisition campaign are limited. However, the significant effect of lower expected retention intention (F-value between 57.165 and 59.630) causes a lower CLV rather soon after campaign introduction. The CLV of "aware, with high attractiveness" customers is significantly higher than the CLV of unaware customers, but only from the fifth year onwards (F-value between 4.669 in year 5), whereas the retention intention is significantly higher (F-value between 71.940 and 87.078) straight from the first year. Even though the revenues are considerably lower (5.4% per year in the first three years) for this group when there is an acquisition campaign; the positive effects of this same campaign on retention intention are larger. All this implies that for the aware customers who rate the acquisition campaign as highly attractive the introduction of an acquisition campaign never harms the CLV and leads to even higher CLV in the longer run.

3.5.3 Simulating value effects due to marketing campaigns

After having established the CLV per customer, we can also make assumptions on the existing customer base's total value effects in response to an acquisition campaign. The base situation column of Table 3.5 shows that, if we assume that an indexed CLV of 100 equals an amount of € 50 and that the focal company has 2 million customers, the total value (in 5 years) is € 380 million ((379.85/100)*50*2million); of which € 302.9 ((379.85/100)*50*2million*80%) million from unaware customers, € 16.0 million from aware customers with low attractiveness ratings, € 35.2 million from aware customers with average attractiveness ratings, and € 25.7 million from aware customers with high attractiveness ratings, respectively). In order to see the effects of a change in either awareness or attractiveness, we perform several simulations. First of all, we simulate the effect of a change in attractiveness ratings: we compute the consequences of the scenario in which 10% of the customers who rates the campaign as averagely attractive would rate

Table 3.5: Simulation of 3 scenarios

	Base Situation	Simulation 1	Simulation 2	Simulation 3
Description		10% of the aware customers thinks the campaign is unattractive instead of averagely attractive	10% of the aware customers thinks the campaign is highly attractive instead of averagely attractive	10% unaware customers are aware, and distributed proportionally overlow, average, and high attractiveness
Percentage of customers per segment				
Unaware	80%	80%	80%	70%
Aware, low attractiveness	5%	6%	5%	7%
Aware, average attractiveness	9%	8%	8%	14%
Aware, high attractiveness	6%	6%	7%	9%
CLV index*				
After 5 years	379.85	379.42	380.28	379.87
Percentage of total CLV after 5 years per attractiveness segment				
Unaware	80%	80%	80%	70%
Aware, low attractiveness	4%	5%	4%	6%
Aware, average attractiveness	9%	8%	8%	14%
Aware, high attractiveness	7%	7%	8%	10%
Hypothetical total value (*1000; after 5 years per segment; assuming: CLV index=100=€50; 2million customers)				
Unaware	€302,921	€302,921	€302,921	€265,872
Aware, lowattr activeness	€16,042	€19,122	€16,042	€23,772
Aware, average attractiveness	€35,155	€31,639	€31,639	€52,093
Aware, high attractiveness	€25,734	€25,734	€29,677	€38,134
Total	€379,853	€379,416	€380,280	€379,870
Resulting gain/loss (vs base situation)		-€436	€427	€17

*Indexed against CLV after 1 year base situation; aggregated over segments the campaign as unattractive (Simulation 1) or highly attractive (Simulation 2). The third simulation deals with the scenario in which an additional 10% of the customers would be aware of the acquisition campaign (30% aware instead of 20%). The 10% extra aware customers are proportionally distributed over the attractiveness segments, e.g. in the base situation 25% of the aware customers gives a low attractiveness rating (5/20=0.25), so in Simulation 3 25% of all additional aware customers is appointed to the aware, low attractiveness segment.

As can be seen from Simulation 1 in Table 3.5, an increase of the low attractiveness group from 5% to 6%, results in a total value decrease of € 436k after 5 years. Even though the total value of the low attractiveness group has gone up by € 3.1 million (€ 19.1 minus € 16.0 million); the loss in value of the average attractiveness group is higher (€ 35.2 minus € 31.6 is -€ 3.5 million). On the other hand, if the same number of customers changes their attractiveness evaluation from average to high, € 3.5 million loss in the average attractiveness segment is amply compensated by the € 3.9 million increase in the segment that rates the campaign as highly attractive. So, simulation 2 results in a positive result of € 380.3 million, €427k higher than the base situation. Simulation 3 (the scenario in which 30% instead of 20% of the customers is aware of the acquisition campaign) changes the value of each segment. The total value of the unaware customers decreases by € 37.0 million, which is sufficiently compensated by the increase in all aware customer segments (€ 7.7 million in the low, € 16.9 million in the average, and € 12.4 million in the high attractiveness group, respectively), leading to a total value increase of € 17k.

The three simulations show the value effect of changed perceptions of the acquisition campaign. If the focal company manages to make the acquisition campaign more attractive to existing customers, total value increases will go up the most. However, if awareness increases by 10% the total value increase is still substantial. On the other hand, if the acquisition campaign is perceived to be unattractive by more customers, total value drops. To summarize, changes in awareness as well as attractiveness ratings considerably influence the total value of the customer base.

3.6 CONCLUSION

In this chapter we examined the effect of attractively priced acquisition campaigns on retention intention, and consequently CLV, of existing customers. We expected that even though acquisition campaigns are not aimed at existing customers, these customers may be aware of the existence of acquisition campaigns and their behavior may be influenced accordingly. We argued that awareness of acquisition campaigns could either positively (Hypothesis 1; e.g., Heath 2007; Vakratsas and Ambler 1999) or negatively (Hypothesis 2; e.g., Hirschman 1970; Xia, Monroe, and Cox 2004) influence retention intentions. In our application we find that awareness as compared to unawareness has a significant positive influence on retention intention, hence Hypothesis 1 is supportted. However, since the policy of the focal company is to give the acquisition discount to complaining customers, the CLV is not only influenced by retention intention, but also by decreased revenues and higher cost to sell due to this complaining. Taking all these effects into account, we reach the conclusion that aware customers do not have a significantly different CLV than unaware customers.

The inclusion of (well-handled) complaining as an independent variable does not change the found effect of awareness on retention intention (Hypothesis 3 is rejected). However, a judgment of campaign attractiveness does influence the CLV of aware versus unaware customers. Campaign attractiveness is positively related to retention intention (Hypothesis 4 is supported), i.e. if the customer thinks the acquisition campaign is unattractive, the retention intention will be lower; and a high attractiveness rating leads to a significantly higher retention intention. The same conclusions can be drawn for the resulting CLV effect. Customers that are aware of acquisition campaigns that they find unattractive have a significantly lower CLV (if the lifetime that is computed with is at least four years), which is mainly due to the lower retention intention. The CLV of aware customers that judge the campaign as highly attractive is significantly higher than the CLV of unaware customers, but only from the fifth year onwards, whereas the retention intention is significantly higher right from the start. Even though the revenues are considerably lower (5.4% per year in the first three years) for this group when there is acquisition campaign; the positive effects of this same campaign on retention intention are much larger.

All in all, attractively priced acquisition campaigns do not seem to harm the (longer term) value of existing customers. So, instead of being offended by the price difference, existing customers tend to be reassured of their choice for the focal company, but only if they think the focal company is making attractive offers. In case of unattractive offers, the acquisition campaigns serve as a trigger to start looking around.

3.7 MANAGERIAL IMPLICATIONS

Our model was empirically tested in the Dutch energy market in cooperation with one of the larger players in this industry. In the assessment of acquisition campaigns, the effects on existing customers so far have not been included, which seems to result in an underestimation of the success of acquisition campaigns. The studied acquisition campaigns turned out to have a positive CLV effect of aware customers versus unaware customers (at least when accounting for attractiveness of the offer). The "offer compensation in case of complaints" policy causes revenues to be lower, but the increased retention effect is large enough to offset the revenue loss. In a nutshell, the focal company is not losing value to existing customers by the introduction of acquisition campaigns. An important remark is that the focal company should always calculate the long term consequences (at least 5 years), because in the short term, the decreased revenues have a larger impact than the increased retention. Simulation of several scenarios shows that an increase in the percentage of customers who think the campaign is highly attractive results in a higher total value. If however, the amount of customers who think the campaign is unattractive goes up, total value will substantially drop. An intermediate increase in total value is found for a 10% increase in awareness. Increasing awareness and/or attractiveness may be difficult. Increased awareness could be realized by higher advertising spending; higher attractiveness perceptions may be the result of deeper discounts or extra features. Which tactic should be chosen depends on the costs needed to realize either the change in awareness or the change in attractiveness rating.

3.8 RESEARCH LIMITATIONS AND FUTURE RESEARCH

In our empirical application we looked at retention intention changes due to awareness of acquisition campaigns in the energy market. The inclusion of actual behavior would give a more realistic picture than the behavioral intention measure used now (Maute and Forrester 1993). For now, however, the percentage of actual churn was too low to be usable. Since the focal company actually ran the acquisition campaigns, the behavioral effects will be measurable in the future.

Furthermore, the CLV computation could be improved by the inclusion of a dynamic retention rate. In the current computation we assume the effects of awareness on retention to be persistent. However, in reality this effect may diminish, or at least change, over time.

It would be interesting to develop a measure to capture dynamic retention intention and include this measure in the CLV computation.

Another limitation is the incomplete set of variables on externalities, such as public opinion, social media, or word-of-mouth. All these externalities may also influence retention intention and CLV (Soscia 2007). Furthermore, we linked awareness to retention and we found a positive effect. Yet, this effect may be larger if we would find a way to measure and include the role of inaction inertia (Arkes, Kung, and Hutzel 2002; Tykocinski, Pittman and Tuttle 1995).

An interesting avenue for future research is the investigation of the effect of competitive offers on retention intention. In the current study we find a negative relation between awareness of the competitive offer and retention intention. It may be the case that customers are looking around on the energy market to find an energy supplier and hence are more likely to be aware of competitive offers. On the other hand, competing offers may also decrease retention intention. Knowing the direction of the negative relation may lead to opportunities to better deal with competition.

A final limitation is the type of campaigns we included in our empirical application. We only studied acquisition campaigns that were based on price promotions. It may well be the case that if these campaigns would focus on other aspects, such as better service, the found effects do not hold.

Chapter 4

The effect of above-the-line and below-the-line communication on acquisition and retention profitability

4.1 INTRODUCTION

Customers are valuable assets for firms, but acquiring and retaining them can be costly. In order to make customers as valuable to the firm as possible, both the complexities of customer relations and the accountability of marketing expenditures need to be understood. Customer relations, acquisition and retention in particular, have been studied extensively in marketing research. Previous studies have focused on the allocation of marketing resources (e.g., Blattberg and Deighton 1996) and the effect of marketing strategies on the future value of acquired customers (e.g., Gupta, Lehmann, and Stuart 2004; Gupta and Zeithaml 2006). Since a lot of money is spent on marketing communication and resources are only limited (Rust, Lemon, and Zeithaml 2004) companies are constantly trying to optimally allocate the available resources. An optimal allocation of resources is realized when the total value of the customer portfolio is maximized.

The range of marketing communication channels among which resources have to be divided has rapidly increased over the past few decades. Especially the advent of the Internet has unlocked a multitude of new opportunities to reach customers (Geyskens, Gielens, and Dekimpe 2002; Henning-Thurau et al. 2010; Neslin et al. 2006; Neslin and Shankar 2009). In general, all marketing communication channels can be divided into 2 categories: above-the-Line (ATL) and below-the-Line (BTL). We approach the difference between ATL and BTL marketing communication channels as a difference in reach (large vs. small). The customer asset management literature recognizes that both ATL and BTL communications create brand awareness, favorable brand associations, and brand preference, potentially increasing customer value (Ambler et al. 2002; Szymanski and Henard 2001). ATL communication channels are in essence mass media, i.e. channels having a massive reach. BTL advertising has a much narrower reach and is more personal, personalized or targeted at specific individuals than ATL. Some BTL channels involve personal contact (e.g. telemarketing, door-to-door selling), whereas others use interpersonal contact methods (e.g. Direct Mail, AdWords). ATL and BTL are likely to influence acquisition and retention profitability, but the direction and size of this influence may differ between these two types of communication efforts. Hence, in this chapter we pose the following research question: How do above-the-line (ATL) and below-the-line (BTL) communication influence acquisition and retention profitability?

Prior research has examined parts of this issue, but to the best of our knowledge, there has not been a comprehensive examination of the effect of marketing resource allocation over ATL and BTL on the interplay between acquisition and retention profitability. Table 4.1 gives an overview of the existing studies. In this table, studies are classified by the inclusion of the link between acquisition and retention activities; the incorporation of profitability or customer equity; the presence of a split between retention and acquisition profitability; and the inclusion of both ATL and BTL. Blattberg and Deighton (1996) developed a model to determine how much to spend on acquisition and retention in order to maximize customer equity. In practice, they use a simple decision calculus to determine the optimal acquisition budget and the optimal retention budget, not really linking acquisition to retention. Berger and Nasr-Bechwati (2001) use Blattberg and Deighton's (1996) framework by assuming a fixed budget and then suggest a model to address how that budget should be allocated between acquisition and retention activities; herein still not including interactions between acquisition and retention. Thomas (2001) was one of the first to present a modeling approach for exploring customer retention that accounts for the impact the customer acquisition process has on the retention process. Yet, this study deals only with relationship duration. Reinartz, Thomas, and Kumar (2005) present a system of equations that links the acquisition and retention processes to customer profitability. Because of the linkage, their system can be used to assess the trade-offs that occur in resource allocation decisions. In addition, they empirically test for the synergistic effect of multiple communication channels on individual consumers' acquisition, retention, and profitability. However, profitability is studied as one outcome and not split in the profitability of acquired versus retained customers. Furthermore, they only look at BTL communication channels and do not include ATL. Rust,

Table 4.1:Comparing this study with existing studies

Study	Studies the link between acquisition and retention?	Includes profitability/ customer equity?	Splits profitability into retention and acquisition profitability	Examines multiple communication channels?	Incorporates competitive spending?
Blattberg & Deighton (1996)	No	Yes	Yes	No	No
Berger & Nasr-Bechwati (2001)	No	Yes	Yes	No	No
Thomas (2001)	Yes	No	No	No	No
Rust, Lemon & Zeithaml (2004)	Yes	Yes	No	Yes	Yes
Reinartz, Thomas & Kumar (2005)	Yes	Yes	No	Yes	No
Villanueva, Yoo & Hanssens (2008)	No	Yes	No	Yes	No
Wiesel, Pauwels & Arts (2011)	No	Yes	No	Yes	No
This study	Yes	Yes	Yes	Yes	Yes

Lemon, and Zeithaml (2004) do make this split by considering the expected lifetime value of both existing customers and prospective customers, thereby incorporating acquisition and retention in the same model. However, their model does not provide for separate or distinct investments in ATL and BTL. Villanueva, Yoo, and Hanssens (2008) do explore the effect of two different acquisition strategies on customer equity growth, but they do not distinguish between acquisition and retention. On the other hand, their study does include BTL as well as ATL communication. Finally, Wiesel, Pauwels, and Arts (2011) study the effect of marketing communication activity on firm profit, accounting for dynamic effects among purchase funnel stages in both off-line and online channels, and feedback effects within and across channels. However, although profit is included, they do not account for the link between acquisition and retention; and look at BTL channels only.

Our study combines several aspects from the abovementioned studies by examining the influence of ATL and BTL marketing communication channels on the profitability of acquired and retained customers, while also considering the mutual relations between these aspects and accounting for competitive expenses. The objectives of this study are to

1. Investigate the relation between retention and acquisition profitability.
2. Examine how retention and acquisition profitability are influenced by ATL and BTL.

We use Vector Autoregressive (VAR) modeling to capture the interconnectedness between retention and acquisition as well as marketing expenditures, and SOV; hereby enabling the estimation of both immediate and longer term (12 months) effects. Again, we empirically test our model in the Dutch energy market in cooperation with one of the larger players in this industry. Understanding how acquisition is related to retention and how to influence this relationship by marketing campaigns provides managers of the focal company with insights into the effects of budget allocation decisions. This tool opens up the possibility of predicting in advance what the long term effect of certain strategies will be on new and existing customers.

The remainder of this chapter is organized as follows. First, we discuss the existing literature and present our conceptual framework. The third section discusses our empirical application and the methodology. Section 4.4 contains the estimation results and simulations, followed by conclusions (Section 4.5), managerial implications (Section 4.6) and research limitations and directions for future research (Section 4.7).

THEORETICAL BACKGROUND

This section describes a framework for examining the influence of above-the-line (ATL) and below-the-line (BTL) on acquisition and retention profitability and how these underlying components create value. As can be seen in Figure 4.1 the value of the customer portfolio is related to the marketing communication mix and competition. The value of the customer portfolio is the combination of profitability of newly acquired customers and profitability of retained customers. Section 4.2.1 discusses the existing literature on these profitability metrics. The included communication mix, being ATL and BTL are discussed in section 4.2.2. Section 4.2.3 examines other findings on the link between customer value, marketing communications and competition.

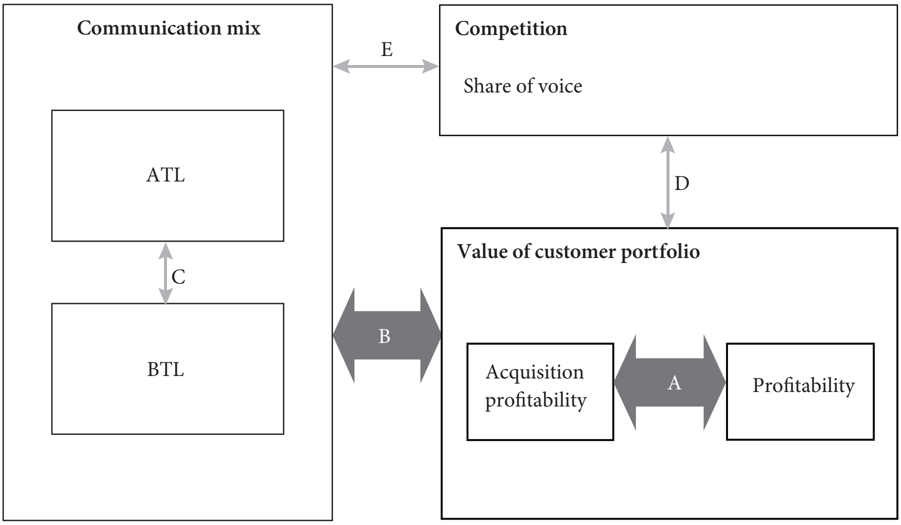


Figure 4.1: Conceptual model

4.2.1 Value of the customer portfolio

Customer value management is the view that customers are a financial asset to companies and should be measured and managed as such (Verhoef, Van Doorn, and Dorotic 2007). Quantification of the value of customers allows marketers to make better evaluations of the effectiveness of marketing actions and a more optimal allocation of a firm's limited resources (Rust, Lemon, and Zeithaml 2004). In the assessment of total value, it is crucial to distinguish between acquisition and retention, and if possible, to jointly consider these two aspects of the customer relationship (e.g., Thomas 2001). Customer retention is believed to offer major benefits to firms, such as improved customer profitability (Jain and Singh 2002) and lowered acquisition costs (Farquhar 2005). Although the importance of long term value creation is recognized by firms, the need to boost short-term indicators of positive business performance is sometimes prevalent and leads to short term sales efforts, i.e. acquisition (e.g., Farquhar 2005; Gupta and Lehmann 2003). Ultimately, firms need to balance their marketing expenditures between acquisition and retention (including up- and cross-sell) in order to maximize customer value (e.g., Berger and Nasr-Bechwati 2001; Blattberg and Deighton 1996; Farquhar 2005). In our model, we operationalize customer value as profitability of both retained and acquired customers. As can be seen in Figure 1, these two components are connected by an arrow (A), because we expect the profitability of all acquired customers to be related to the profitability of all retained customers. More specifically, since acquired customers of today form the future retention base, the profitability of the acquired customers directly influences the retention profitability in later periods (Lewis 2006).

4.2.2 Communication mix

As previously stated, all marketing communication channels can be divided into 2 categories: above-the-Line (ATL) and below-the-Line (BTL). ATL communication channels are in essence mass media, i.e. channels having a massive reach. Several studies have established a positive (but small) relation between ATL advertising and sales (Assmus, Farley, and Lehmann 1984; Dertouzos and Garber 2006; Hu, Lodish, and Krieger 2007, 2009; Leone 1995; Sethuraman, Tellis, and Briesch 2011; Tellis, Chandy, and Thaivanich 2000; Winer 1979, 1980). However, there has been no general agreement on the duration of the positive effect of ATL on sales (Vakratsas and Ambler 1999); and on the size of the average elasticities (Assmus, Farley, and Lehmann 1984; Lodish et al. 1995; Sethuraman, Tellis, and Briesch 2011). A caveat of these studies is that almost none of them investigates the effects of advertising in contractual or service settings. The only study to include service (Sethuraman, Tellis, and Briesch 2011) does not find a significant influence of ATL advertising on sales. Another interesting learning from the literature is that sales are hardly ever split into acquisition and retention. Hence, it is hard to say in advance how ATL specifically affects retention and acquisition profitability. On the other hand, it has been found that ATL positively influences customer satisfaction (Baidya and Basu 2008), which may increase brand loyalty and consequently may have a long term effect on retention profitability (Polo, Sese, and Verhoef 2011). Yet, other studies find that ATL does not increase the number of retained customers (Deighton, Henderson, and Neslin 1994), but does positively influence the profitability per retained customer (Tellis 1988).

BTL advertising has a much narrower reach and is more personal, personalized or targeted at specific individuals than ATL. Previous research asserts that more interpersonal contact channels have higher conversion rates than less interpersonal contact channels (Anderson and Narus 1999; Baidya and Basu 2008; Coppett and Staples 1993; Sargeant and Hudson 2008). However, less interpersonal contact channels are still positively related to sales (Wiesel, Pauwels and Arts 2011). Although positive, the effect of BTL on sales only appears to be present in the short run (Wiesel, Pauwels, and Arts 2011). In this literature also, a distinction between acquisition and retention is not made. An exception being a study by Deighton, Henderson, and Neslin (1994), who come to the conclusion that advertising does not lead to repeat purchases.

All in all, ATL and BTL are expected to influence sales, both in the short and in the longer run. Short term BTL effects on sales are supposedly larger than ATL effects on sales (Deighton, Henderson, and Neslin 1994; Tellis 1988; Vakratsas and Ambler 1999). However, it could be that BTL communication creates higher acquisition than ATL communication, whereas ATL has a more positive influence on customer retention (or the other way around). Our empirical application gives insight into these effects of ATL and BTL on acquisition and retention profitability.

4.2.3 Other effects on value of the customer portfolio

As discussed, both ATL and BTL may influence customer value. However, these marketing communication channels may also influence each other (as indicated by arrow C in Figure 4.1; Olson and Thjømøe 2009; Naik and Raman 2003; Wiesel, Pauwels, and Arts 2011; Radio Advertising Bureau 2011). Increased spending on ATL may lead to decreased BTL spending because of budget constraints, but may also lead to higher BTL spending because a firm may believe that increased spending in both channels may lead to better results.

Furthermore, several studies have identified feedback loops, i.e. the effect of sales on advertising, which is caused by the effect of advertising on sales (e.g. Bass 1969; Ashley, Granger, and Schmalensee 1980). After marketing communication has affected the total value, the marketing communication mix in following periods may be adjusted accordingly. Therefore it is expected that marketing activities through the ATL and BTL channels and the total value of the customer portfolio are related in a bi-directional way (arrow B in Figure 4.1).

Finally, the effect of the marketing communication mix on customer value cannot be viewed in isolation, but is also influenced by competition (arrow D in Figure 4.1; Rust, Lemon, and Zeithaml 2004). Competition is shown to be an important driver of customer behavior (Polo, Sese, and Verhoef 2011). In addition, competitive spending is influenced by spending of other companies in the market and in turn influences the communication spending of these companies (Arrow E in Figure 4.1). Consequently, we also incorporated competition in our model, by including the share-of-voice.

4.3 EMPIRICAL APPLICATION

4.3.1 Data description

For this study data from the focal company's customer database is combined with the focal company's accountancy data, and external media spending data. The included customer data contains information on the total profitability of acquired and retained customers. For this study, profitability in a specific month has been computed as:

$$\textit{Acquisition Profit}_t = \sum_{a=1}^{A} (\textit{Revenues}_{at} \text{-} \textit{Sales Costs}_{at}) \tag{4.1}$$

where

- *Acquisition Profit*$_t$ is the sum of the profitability of all acquired customers in month *t*;
- *Revenues*$_{at}$ are the revenues of acquired customer *a* in month *t*;
- *Service Costs*$_{at}$ are the service costs (i.e. payment enforcement costs and contact costs) of acquired customer *a* in month *t*.

And:

$$\textit{Retention Profit}_t = \sum_{r=1}^{R} (\textit{Revenues}_{rt} \text{-} \textit{Sales Costs}_{rt}) \tag{4.2}$$

where

- *Retention Profit*$_t$ is the sum of the profitability of all retained customers in month *t*;
- *Revenues*$_{rt}$ are the revenues of retained customer *r* in month *t*;
- *Service Costs*$_{rt}$ are the service costs (i.e. payment enforcement costs and contact costs) of retained customer *r* in month *t*.

Furthermore, the accountancy data provides us with ATL as well as BTL expenditures. The external media spending data (from Mediaedge:cia) shows the share-of-voice of the focal company, i.e. the focal firm's advertising weight expressed as a percentage of the total energy market's advertising weight in a given time period.

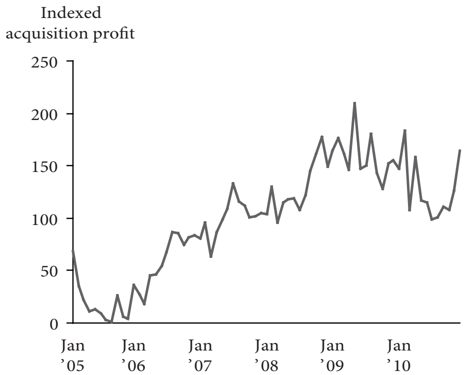
All data has been collected for every month starting January 2005 up until December 2010. Monthly data seem appropriate (Dertouzos and Garber 2006) since the focal company's advertising decisions are made per month. In addition, all data are aggregated over geographical areas (assuming that advertising intensities are constant over space) and over groups of customers (acquired and retained). With the aggregation over customers, we acknowledge that any differences in advertising responsiveness that channels might have on individual customers are not included.

Figure 4.2 shows the development of each of the variables in our dataset over time. As Figure 4.2a shows there is an upward trend in the profitability of acquired customers. The retention profitability seems to be relatively stable (see Figure 4.2b). From Figure 4.2c it can be read that ATL expenditures show quite some variation, but look stable in the long run; BTL (4.2d) expenditures have increased between 2005 and the beginning of 2009 and have slowly declined since 2009; and SOV (4.2e) is stable over time, with values between 1% and 80% and an average of 25%.

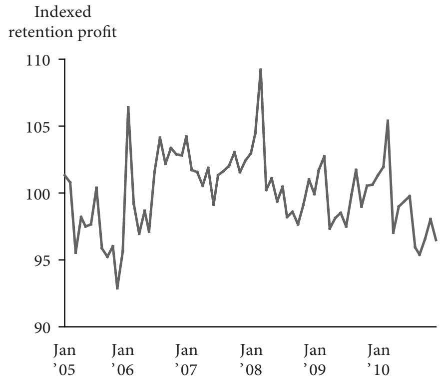
Remarkably, the graphs of BTL spending and acquisition profitability have a very similar shape. A closer examination of these two variables shows that their correlation is 0.8, which is extremely high. An explanation for this, as given by the focal company, is that the majority of BTL spending for acquisition is paid only after the customer has been acquired (a so called "no cure-no pay" strategy). In other words, for every customer that is acquired, a fixed amount is added to BTL spending. This fact makes further examination of the effect of BTL spending on acquisition rather unreliable. Therefore, we decided not to further examine the effect of BTL on both acquisition and retention profitability. However, we keep BTL spending in our model, because of the expected relation between BTL and ATL.

4.3.2 Research methodology

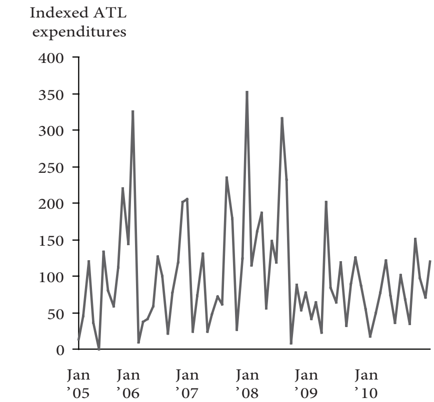
In order to estimate the effect of the marketing communication mix on customer value (and vice versa) we use a Vector Autoregressive (VAR) model. The main advantage of a VAR model is that it is a time series model in which all the variables are regressed against their values of *n* preceding periods. This means that one can predict as far into the future as one wants by inputting all the calculated results back into the model (Schlegel 1985; Hanssens,



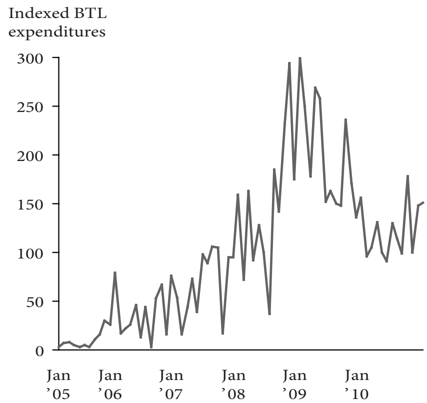
a: Profitability of acquired customers



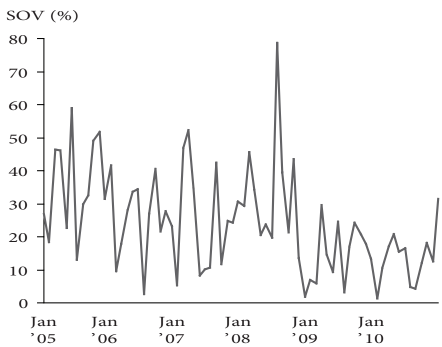
b: Profitability of retained customers



c: ATL expenditures (indexed against mean)



d: BTL expenditures (indexed against mean)



e: Share of voice

Figure 4.2: Development of variables over time

Parsons, and Schultz 2003). Before a VAR model can be specified, Granger causality tests have to be performed to determine which variables are temporally causing which other variables (Leeflang et al. 2000; Hanssens, Parsons, and Schultz 2003), i.e. which variables should be included as endogenous variables (Wiesel, Pauwels, and Arts 2011). In addition, it should be checked whether the included variables are stationary or evolving over time (unit root test; e.g., Enders 2004).

Based on the Granger causality and unit root tests, we can specify a VAR model including acquisition profitability, retention profitability, ATL spending, BTL spending, and SOV. All variables are endogenous and hence we capture direct, indirect and feedback effects of marketing communication and competition on customer value. Equation 2 presents this model:

$$\begin{bmatrix} Acquisition\ Profit_t \\ Retention\ Profit_t \\ ATL_t \\ BTL_t \\ SOVt \end{bmatrix} = a + \sum_{k=1}^{K} B_k \begin{bmatrix} Acquisition\ Profit_{t\text{-}k} \\ Retention\ Profit_{t\text{-}k} \\ ATL_{t\text{-}k} \\ BTL_{t\text{-}k} \\ SOVt\text{-}k \end{bmatrix} + e_t, t+1,\ldots,T \tag{4.3}$$

where

- *Acquisition* $Profit_t$ is the profitability of all acquired customers in month t;
- *Retention* $Profit_t$ is the profitability of all retained customers in month t;
- ATL_t is the € amount of ATL expenditures in month t,
- BTL_t is the € amount of BTL expenditures in month t,
- SOV_t is the share of voice of the company in month t,
- a is the vector of intercepts,
- B_k is the vector of estimation coefficients,
- e_t is the vector of error terms.

4.4 RESULTS

The Granger Causality tests (Granger 1969) re-establishes that acquisition profitability is caused by BTL; and shows that retention profitability is caused by ATL. Furthermore we find that the profit of acquisition causes the profit of retention Finally, ATL, BTL and SOV are caused by each other and acquisition and retention profitability. From the correlation matrix in Table 4.2 we can read the current period direction of the abovementioned effects.

The Augmented Dickey-Fuller unit root tests revealed that both acquisition profitability and BTL have a unit root. However, regardless of the included assumptions, the Johansen cointegration test (Johansen et al. 2000) shows that the number of cointegrating relations between BTL and acquisition profitability is zero. Hence, our VAR model is estimated with these two variables in differences. As suggested by the Schwartz Information Criterion (BIC) we estimate the VAR models with one lag. The models explain 32.6% of the variance in differenced acquisition profitability (adjusted R-squared=0.27), and 49.9% (adjusted R-squared=0.46) of the variance in retention profitability.

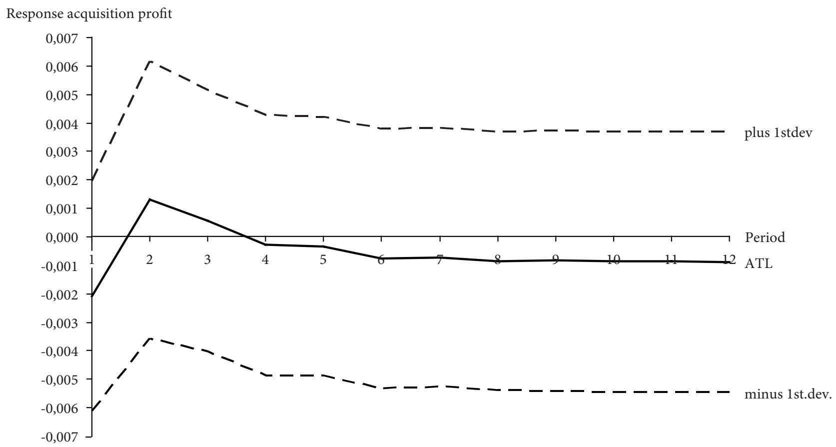
Table 4.2: Correlations between variables in the VAR model

	Acquisition profitability	Retention profitability	ATL	BTL	SOV
Acquisition profitability	1.00	0.18	-0.08	0.80	-0.43
Retention profitability	0.18	1.00	-0.05	-0.02	-0.10
ATL	-0.08	-0.05	1.00	0.04	0.31
BTL	0.80	-0.02	0.04	1.00	-0.18
SOV	-0.43	-0.10	0.31	-0.18	1.00

4.4.1 Effect of ATL on the value of the customer portfolio

Based on the VAR-estimates, we calculate the generalized impulse response of both acquisition[17] and retention profitability to a one-unit change in ATL, hereby incorporating all other underlying effects, i.e. all relations in our model. Figure 4.4 shows a graphical representation of the impulse response functions. As can be seen from Figure 4.4a, ATL does not significantly (within a 68% confidence interval, Dekimpe and Hanssens 1999) influence acquisition profitability. Retention profits, on the other hand, are influenced by ATL communications from the second up until the fifth month (see Figure 4.4b). In these 4 months, ceteris paribus, an additional €1 million spending in ATL results in €580k extra retention profit. Hence, the return on ATL investment is found to be negative.

a: (Accumulated) response of acquisition profit to generalized one S.D. increase in ATL



b: Response of retention profit to generalized one S.D. increase in ATL

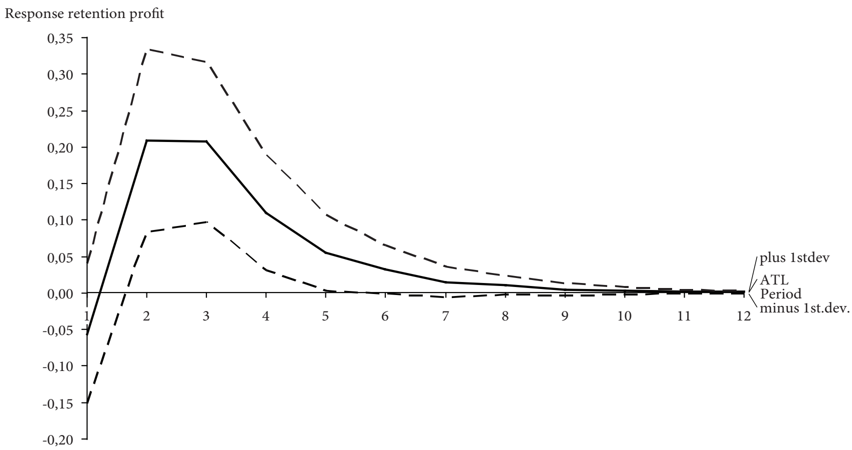


Figure 4.4: Response to generalized one S.D. increase in ATL

4.4.2 Interplay between the customer value components

In addition to estimating the effects of ATL on value, the VAR-model allows us to calculate the response of each endogenous variable to each other endogenous variable, e.g. to quantify the relations between acquisition and retention profitability. Table 4.3 shows the immediate (first month) as well as the cumulative unit effects (over 12 months) of the value components to themselves and the other value component. As can be seen from the diagonal of Table 4.3, both

Table 4.3: Impulse-response results for all variables in the VAR system

		Response				
		Acquisition profitability (accumulated)	**Retention profitability**	**ATL**	**BTL**	**SOV**
Impulse (1 s.d.)	**Acquisition profitability**					
	Immediate unit effect	+	n.s.	n.s.	n.r.	-
	Cumulative unit effect	+	+	n.s.	n.r.	-
	Retention profitability					
	Immediate unit effect	n.s.*	+	n.s.	n.r.	-
	Cumulative unit effect	-	+	n.s.	n.r.	-
	ATL					
	Immediate unit effect	n.s.	n.s.	+	+	+
	Cumulative unit effect	n.s.	+	+	+	+
	BTL					
	Immediate unit effect	n.r.**	n.r.	+	+	+
	Cumulative unit effect	n.r.	n.r.	+	+	+
	SOV					
	Immediate unit effect	-	-	+	+	+
	Cumulative unit effect	-	-	+	+	+

*not significant at 68%
**not reliable because of inherent dependency between BTL and acquisition

acquisition and retention profitability are positively influenced by their own past, both in the short and in the long run.

Furthermore, acquisition profitability is negatively influenced by retention profitability. So, it may be that higher profitability of retained customers serves as an incentive for the company to increase acquisition discounts and consequently decrease acquisition profitability. Finally, the effect of acquisition profit on retention profit is positive, indicating that acquiring at high profits (i.e. higher margins or lower costs) leads to higher profitability of those customers who are retained.

4.4.3 Other effects

In our conceptual model we assumed feedback effects between the value components and marketing communication (arrow B in Figure 1), as well as a mutual relation between ATL and BTL spending (arrow C in Figure 1), and a two-way effect between SOV and value (arrow D in Figure 1) and SOV and marketing communication (arrow E in Figure 1). Table 4.3 shows the VAR-model impulse response results with respect to these relations. As can be seen from Table 4.3, there are no significant feedback effects of acquisition and retention profits on ATL. However, ATL is positively reinforced by itself, i.e. ATL spending leads to ATL spending. Furthermore, increased BTL spending causes higher ATL spending. BTL spending increases as a result of ATL spending, and itself. The reinforcing effects of BTL and ATL on itself could be explained by the idea that successful strategies tend to be continued, so success with ATL/BTL now results in more ATL/BTL spending in order to be more successful in the future. The positive effects between ATL and BTL reflect the expectation of reinforcing effects: ATL precedes BTL in order to generate higher sales.

Finally, we find a negative effect of SOV on both acquisition and retention profitability (and the other way around) and a positive effect of SOV on ATL and BTL spending, as well as a positive effect of ATL and BTL on SOV. The negative effect may be due to the lower prices the company offers when relative spending increases. If the company invests money to increase the SOV, this probably coincides with lower prices, hence lower profitability. The positive effect is rather logical, the more the company spends, the more likely it is to spend more than its competitors.

4.4.4 Model checks

To test the validity of our model we checked the results by checking for residual autocorrelation; and by examining the effects of a change in VAR lag specification. Residual serial correlation is tested for with the Portmanteau test. Since we do not find significant effects for any of the 12 lags, we conclude that there is no residual autocorrelation in our model. Estimation of the VAR-model of Equation 4.3 with 2 and 3 lags yields very similar results (effect sizes differ slightly, but signs are identical), whereas the estimation efficiency declines. So, we find no reason to suspect that our results are driven by the lag order specification.

4.5 CONCLUSION

This study looked at the effect of various marketing communication efforts (ATL and BTL) on the total value of the customer portfolio. We estimated a VAR-model in order to investigate both the short term and the longer term relation between retention and acquisition profitability, while accounting for ATL and BTL spending and competition. The direct effect of BTL on profitability could not be included because of the spurious relation between BTL spending and acquisition profitability. The effects of ATL on profitability could be estimated (accounting for the BTL and SOV effects); and our findings suggest that the return on ATL investments is negative: there is no effect for acquisition profitability and € 0.58 retention profit for every €1 spent on ATL. The absence of an effect of ATL on acquisition profitability is in line with the findings of Tellis and Weiss (1995), but contradicts other findings from previous studies, which suggest that there is a positive (but small) relation between ATL advertising and sales (Hu, Lodish, and Krieger 2007, 2009; Sethuraman, Tellis, and Briesch 2011; Tellis, Chandy, and Thaivanich 2000). The lack of an effect of ATL on acquisition may be due to the way in which the ATL campaigns are designed: there is no call for action, so acquisition is not really facilitated. The fact that ATL is more effective for increasing retention profit is intuitively correct, since ATL is used to create brand awareness and hence may enhance customer retention (Polo, Sese, and Verhoef 2011) and (less so) acquisition. On the other hand, ATL may cause awareness of lower priced products (promoted in order to acquire customers) resulting in lower profitability per retained customer, which may explain a ROI of -42%.

Furthermore, we find that acquisition and retention profitability are positively affected by their own pasts. More interestingly, from the ninth month onwards, retention profitability has a negative effect on acquisition. And, from the second to the seventh month, acquisition profit has a positive effect on retention profit. This may imply that the profitability of retained customers may have changed the price setting of acquisition campaigns, resulting in lower acquisition profits. However, if the aim of the company is to have higher long term retention profits these lower acquisition profits are not beneficial, because lower acquisition profits result in lower retention profits.

Unlike previous studies (e.g. Bass 1969; Ashley, Granger, and Schmalensee 1980), we find no evidence of significant feedback effects of acquisition and retention profits on ATL. Yet, ATL is influenced by BTL spending: ATL spending increases when BTL spending increases. BTL spending in turn increases as a result of increased ATL spending. The positive effect of ATL and BTL may indicate the expectation of reinforcing effects (e.g. Naik and Raman 2003; Wiesel, Pauwels, and Arts 2011): ATL precedes BTL in order to generate higher sales. The reinforcing effects of BTL and ATL on itself could be explained by the idea that successful strategies tend to be continued. Remarkably, we cannot identify a trade-off in the decisions between ATL and BTL spending (which would have been indicated by a negative sign), i.e. it seems like spending more on ATL does not lead to the decision to spend less on BTL.

Finally, in accordance to Rust, Lemon, and Zeithaml (2004), we find a negative relation between SOV and both acquisition and retention profitability and a positive relation between SOV, ATL, and BTL spending. The former relation may be due to marketing strategy: investing more money to increase the SOV may coincide with lower prices, hence lower profitability. The latter relation is rather logical, the more the company spends, the more likely it is to spend more than its competitors.

4.6 MANAGERIAL IMPLICATIONS

Since we assume that management wants to know the return on their investments (Johnson and Gustafsson 2000), we developed a framework that enables this quantification. Our framework, which is much simpler than for example the framework of Reinartz, Thomas, and Kumar (2005), shows the effect of additional spending in ATL on acquisition and retention profitability. This effect not only includes the direct link between ATL and the profitability variables, but simultaneously includes the interplay between acquisition profitability, retention profitability, ATL, BTL, and SOV. With this framework it is rather straightforward to predict in advance what the long term effect of certain strategies will be on new and existing customers.

An additional investment in ATL showed to have a negative return The return on investment may be increased by either enabling a higher profitability per acquired or retained customer or higher acquisition or retention numbers. Since ATL does not significantly influence acquisition profitability, another strategy should be employed for acquiring than for retaining customers. It would be interesting to see if the content of ATL (promote acquisition offers or not) changes the profitability of retained customers.

4.7 RESEARCH LIMITATIONS AND FUTURE RESEARCH

In our empirical application we looked at the interplay between acquisition profit, retention profit, ATL, BTL and SOV in the energy market. We find that the ROI of ATL is negative. It may be interesting to see which component of profitability causes this. In order to see this, it may be necessary to disentangle profitability into its underlying components: revenues, service costs and the number of acquired or retained customers. Including all these components may yield a richer picture. However, including more components in the VAR-model results in a large increase in the number of parameters to be estimated. Hence, probably more data points are needed. These data points will be created as time advances, making this analysis possible in the future.

Another limitation of our study lies in the relation between BTL and acquisition numbers (and thus acquisition profitability). Since the focal company pays for acquired customers only once they actually have been acquired, it is hard to say which variable is in reality causing which other variable. Therefore, we were not able to incorporate this relation directly. It would be interesting to find a way in which BTL could be included in a similar fashion as ATL.

To end with, it should be noted that the relations that were found in our model may be (service) industry specific or specific for contractual settings. Therefore similar studies should be performed in other industries and (non-)contractual settings to test whether the found effects are generalizable.

Chapter 5

Conclusions and future research

5.1 INTRODUCTION

Customers are very valuable for companies, but since resources are limited, firms constantly need to consider which consumers are worth their money. In some cases it may be very fruitful to increase the value of the customers who are already in their base, whereas in other situations it may be wiser to grow the customer base by acquiring new customers. In this thesis we focused on both the valuation of retained customers and budget allocation decisions between acquisition and retention.

Throughout this thesis, we have focused on customer value issues in the energy market. In this chapter, we provide answers to the research questions formulated in Chapter 1. We summarize the main conclusions of our three studies, and discuss the managerial implications of our findings. Then we elaborate on the usability of our results in the actual business context. We conclude this chapter with several potential avenues for future research, both based on the studies we did and on ideas we think are worthwhile studying in the energy market in general.

5.2 MAIN FINDINGS

5.2.1 Customer value modeling and a practical application for marketing decision making

In marketing literature several customer lifetime value (CLV) models can be found. Most include retention, revenues and direct marketing costs. In this study we contribute to the existing literature on CLV by including service costs as value detractors and credit risk as revenue risk. We show that, in our study context, customer value should include not only revenues, but also service costs and credit risk. In addition, this study provided a general framework for using the outcomes of the customer value model in general marketing decision making. Of particular interest are the resulting value consequences of marketing actions. We simulated the consequences of four different actions and showed how a combination of changed customer value due to the action and the success probability of that action leads to a simulation value per customer, which can be used to identify the most suitable action for each customer.

5.2.2 The effect of acquisition campaigns on existing customers' CLV

In Chapter 3 we examined the effect of attractively priced acquisition campaigns on retention intention, and consequently CLV, of existing customers. We find that customers who are aware of the acquisition campaigns have a significantly higher intention to stay than customers who are unaware of these campaigns. However, since the policy of the focal company is to give the acquisition discount to complaining customers, the CLV is not only influenced by retention intention, but also by decreased revenues and higher cost to sell due to this complaining. Taking all this into account, we reach the conclusion that aware customers do not have a significantly different CLV than unaware customers. On the other hand, if we include the attractiveness of the offer as an additional explanatory variable, we find a positive effect of campaign attractiveness on retention intention, i.e. if the customer thinks the acquisition campaign is attractive the retention intention will be higher. The same conclusions can be drawn for the resulting CLV effect: customers that are aware of acquisition campaigns that they find unattractive have a significantly lower CLV, whereas customers that judge the campaign as highly attractive have a significantly higher CLV. All in all, attractively priced acquisition campaigns do not seem to harm the (longer term) value of existing customers.

5.2.3 The effect of ATL and BTL on acquisition and retention profitability

This study looked at the effect of above-the-line (ATL) and below-the-line (BTL) efforts on the total value of the customer portfolio. We estimated a VAR-model in order to investigate both the short term and the longer term relation between retention and acquisition profitability, while accounting for ATL and BTL spending and competition. The direct effect of BTL on profitability could not be included because of the spurious relation between BTL spending and acquisition profitability. The effects of ATL on profitability could be estimated (accounting for the BTL and SOV effects); and our findings suggest that the return on ATL investments is negative, i.e. spending an additional €1 million will not result in a return of this size. With respect to the relation between acquisition profitability and retention profitability, we find that retention profitability has a negative effect on acquisition profitability, whereas acquisition profit has a positive effect on retention profit. We find no evidence of significant feedback effects of acquisition and retention profits on ATL. Yet, ATL spending increases when BTL spending increases. BTL spending in turn increases as a result of increased ATL spending. Finally, we find a negative relation between SOV and both acquisition and retention profitability and a positive relation between SOV, ATL, and BTL spending.

5.3 MANAGERIAL IMPLICATIONS AND USABILITY

5.3.1 Implications for managers

In all three studies of this thesis the research question was based on real-life questions at the focal company. Therefore, the results should provide the managers with valuable insights. From the study in Chapter 2, managers of the focal company know which components influence customer value: revenues and retention are important, but credit losses and service costs are also a very relevant side of the equation to include. Moreover, since we simulated the consequences of several marketing actions, we are able to assess the effects of marketing actions on customer value. Based on these simulations, we can define a most suitable action per customer, which enables the focal company to consider all aspects of profitability before deciding whether or not to target a customer for a specific action. All in all, with our customer value model and the implications it has for marketing decision making, the focal company now has the possibility to increase profitability of its customer base. Targeted marketing actions for individual customers or groups of customers increases value, if the right action is assigned to the right customer. So, our customer value model is a valuable tool for maximizing customer value.

The findings of Chapter 3, which are that acquisition campaigns have a positive effect on the CLV of aware customers (at least when accounting for attractiveness of the offer), imply that the risk of offering promotional acquisition deals is not as high as expected. However, this does not mean that any campaign will have the same results, as variation in attractiveness or tone of voice of the campaign may lead to different results. Furthermore, the "offer compensation in case of complaints" policy causes revenues to be lower, but the increased retention effect is large enough to offset the revenue loss. The company may consider changing this policy; however it does not necessarily need to do so. Finally, simulation of several scenarios shows that an increase in the percentage of customers that thinks the campaign is highly attractive results in a higher total value. If however, the amount of customers that thinks the campaign is unattractive goes up, total value will substantially drop. An intermediate increase in total value is found for a 10% increase in awareness. Increasing awareness and/or attractiveness may be difficult. Increased awareness could be realized by higher advertising spending; higher attractiveness perceptions may be the result of deeper discounts or extra features. Which tactic should be chosen depends on the costs needed to realize either the change in awareness or the change in attractiveness rating.

Finally, understanding how acquisition is related to retention and how to influence this relationship by marketing campaigns, as studied in Chapter 4, provides managers with a means to facilitate budget allocation. This tool opens up the possibility of predicting in advance what the long term effect of certain strategies will be on new and existing customers. Investments in ATL showed to have a negative return on investment . This return on investment may be increased by either enabling a higher profitability per acquired or retained customer or higher acquisition or retention numbers. ATL campaigns could be used to increase the profitability of retained customers. It would be interesting to see if the content of ATL (promote acquisition offers or not) changes this retention profitability. Since ATL does not significantly influence acquisition profitability, another strategy should be employed for acquiring than for retaining customers.

5.3.2 Usability of the results

Since all three studies of this thesis were based on questions from the focal company, we will elaborate on the way in which our results can be (or have been) implemented at this company. First of all, the results of Chapter 2 led to a change from calculating customer value to predicting customer value and making marketing decisions based on simulations. Our model has been used to identify a best action per customer and these actions have been conducted. Although the results were promising, much remains to be learned. Especially the exact way in which to conduct a campaign remains a challenge.

Chapter 3 shows that the effects of acquisition campaigns on existing customers need not be negative. This insight is comforting for some managers. However, a condition for the positive effect is a high evaluation of attractiveness of the campaign. This learning can easily be incorporated in future acquisition campaigns.

Chapter 4 is somewhat harder to implement. A VAR model is mainly a descriptive modeling instrument, i.e. it describes what happens to Y as a consequence of a change in X, which changed based on Y in the previous period. Our model provides insights into the way both the company and consumers make decisions. Since every variable in the model influences every other variable, the results are hard to explain. However, if we accept the model as a black-box, it offers a nice tool to compute what-if scenarios.

To conclude, both the studies in Chapter 2 and Chapter 3 are, or could be, easily implemented at the focal company. The model in Chapter 4 provides valuable insights, but is somewhat harder to employ in practice.

5.4 FUTURE RESEARCH PERSPECTIVES

5.4.1 Research perspectives based on our work

In this section we provide several topics that may be interesting to study in future work. In Chapter 2, we presented a rich customer value model; however, such a model requires a lot of customer data. This data was available for some years, but if we would have had customer data over a longer time span, we could have validated the stability of our customer value model over time. Future studies could include these extra years to see if the customer value components remain relevant over time and to verify the stability of the individual models.

In addition, our study in Chapter 2 identifies the best action per customer. A challenge may lie in lack of experience in designing specific marketing actions that give the expected results, especially so for service costs, credit risk and retention. More qualitative marketing research may identify specific actions for these purposes.

In our study of the effect of acquisition campaigns on existing customers, we looked at retention intention changes due to awareness in the energy market. The inclusion of actual behavior would give a more realistic picture than the behavioral intention measure used now. Since the focal company actually ran the acquisition campaigns, the behavioral effects will be measurable in the future. Once these data are available, it would be very interesting to see if intention and actual behavior are alike, or if differences occur.

Furthermore, the type of campaigns we included in our study on the effects of acquisition campaigns were all based on price promotions. It may well be the case that if these campaigns would focus on other aspects, such as better service, the found effects do not hold. It would be challenging to study this. In relation to this, it may also be fascinating to look at the effects of another way of presenting the acquisition campaign, i.e. the tone of voice.

In our study on the effect of ATL and BTL on the interplay between acquisition profit and retention profit, we find that the ROI of ATL is negative. It may be interesting to see which component of profitability causes this. In order to draw conclusions about this, it may be necessary to disentangle profitability into its underlying components: revenues, service costs and the number of acquired or retained customers. Including all these components may yield a richer picture.

A limitation of the study in Chapter 4 lies in the relation between BTL and acquisition numbers (and thus acquisition profitability). Since the focal company pays for acquired customers only once they actually have been acquired, it is hard to say which variable is in reality causing which other variable. Therefore, we were not able to incorporate this relation directly. It would be interesting to find a way in which BTL could be included in a similar fashion as ATL.

Finally, it would be valuable to replicate our studies at other companies, in other industries, at other times. Results that were found in our models may be (service) industry specific. Therefore similar studies should be performed in other industries to test whether the found effects are generalizable.

5.4.2 General ideas for future research in the energy market

This thesis answers some customer value issues in the energy market. However, the energy market, just like other recently liberalized markets, opens up possibilities for many other interesting value-related studies. First of all, in our studies, we mainly used data from transactions with customers or hard measures. Future research could study value resulting from customer engagement, satisfaction or environmental factors. Incorporating the "softer side" of the customer relation may yield even richer models (Kumar et al. 2010).

Another nice topic to study would be the effect of social media on customer value. The use of social media is rapidly increasing (Libai et al. 2010), leading to several influences on customer behavior. First of all, customer behavior is influenced by the behavior of other people in their (digital) social network. Secondly, companies influence the behavior of people by advertising through social media. Both influences may affect customer value.

Furthermore, durable energy is a hot topic in the energy market, as in many other markets. Market research at the focal company finds that consumers indicate that they would like to act in an environmental friendly (green) manner. However, in practice, only a small percentage of customers actually choose to do so. It would be worthwhile to investigate the barriers to actually living up to the green preferences.

Finally, we think it would be very nice to investigate several pricing issues in the energy market. Many competitors entered the market with low prices (price-fighters), a strategy aimed at acquiring new customers. A similar strategy is adopted by companies that function as intermediaries to get the best price from all energy companies. Both these price-fighters and intermediaries possibly influence the behavior of consumers. Some may switch, whereas others may remain passive. Each type of behavior may influence the CLV of these customers. It would be a challenge to quantify these influences. Furthermore, almost all energy companies change their prices (bi-) annually, because of changes in the oil prices. These price-changes may change customer behavior, and consequently, CLV. On the other hand, it is also possible that customers just accept price changes, maybe because these changes are communicated about in an appealing manner. It would be interesting to study the effect of price changes and the communication about these changes on CLV.

All in all, we hope that this thesis inspires other researchers to further investigate value issues in recently liberalized markets. In addition, we would be very happy if this thesis inspires managers at the focal company to incorporate our findings in their business plans and stirs up curiosity for more related research.

Notes

1. Each type of contract has its own gross margin. This margin may in practice vary over time. In our customer value model, however, it has been kept constant to avoid unnecessary complexity.
2. Energy usage appears to show little variation over time, and therefore an average energy usage per customer (i) can be taken.
3. Predicting the exact number of payment enforcements a customer receives did not lead to accurate results, neither with linear regression, nor with a count model such as Poisson regression.
4. We do not have information on who is and who is not paying after all.
5. The desciptive statistics of the validation samples are not significantly different.
6. The exact estimations can be found in Appendix 2.A.
7. As can be seen in Table 2.4 the MedAPE for Model B1 is 0. This means that for at least 50% of the customers the value of last year equals the value of this year. (pg 29)
8. We believe that the more likely it is that customers have payment enforcement costs, the less likely it is an action will change the customer's payment behavior.
9. To make sure that retention intention is not subject to measurement error we developed several versions of the survey in which the order of the questions is varied. These versions can be included in our model as potential covariates.
10. A comparison of the respondents and the control group (a group of customers who were customers at the time of selection and for whom an e-mail address was available, but were not actually approached) shows that on 180 relationship and socio-demographic characteristics there are no significant differences. However, respondents have a slightly different product portfolio, are slightly older, have a little less payment issues, and are indicated to be somewhat more frequent internet users. Despite these small differences, in general, we conclude that the respondents are representative for the customer base.
11. LOGIT_RETENTION= LOG((Retention Intention/100)/(1-(Retention Intention/100))); where in 7% of the cases Retention Intention has been set to 0.01 in case of 0% intention and 0.99 in case of 100% intention.
12. Since we are not studying nested models, it is hard to determine whether the change in R-squared is significant.

13. $$\textit{Residual (for binary logistic model)}=\frac{\textit{Actual value - Predicted value}}{\sqrt{\textit{Predicted value (1-Predicted value)}}}$$

where

- Actual value is 0 (unaware) or 1 (aware)
- Predicted value is the predicted probability that a customer will be aware.

14. This model is a simplified version of the CV model we developed in Chapter 2.
15. Scaled retention intention has been computed as follows:

$$\textit{Scaled Retention Intention}=\textit{Retention Intention}+x(1\textit{-Retention Intention})$$

$$\textit{where:}\quad x=\frac{\textit{Actual Retention - Retention Intention}}{(1\textit{-Retention Intention})}$$

For example: assume x=0.4; then: if the retention intention is 72%, the scaled retention intention=0.72+0.4*(1-0.72)=0.83.

16. An examination of customer characteristics (e.g. revenues) reveals that in case of no acquisition campaign, the differences between aware and unaware customers are not significant; the same holds for the different attractiveness segments and unaware customers.
17. For acquisition we used the accumulated response, because in the model it is included in differences.

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Samenvatting (Summary in Dutch)

Klanten zijn het meest waardevolle bezit van bedrijven, maar zowel het behouden als het verwerven ervan gaat maar zelden moeiteloos. Omdat budgetten beperkt zijn, zullen veel bedrijven goed nadenken over de balans tussen klantbehoud en klantwerving. Het behouden van klanten heeft grote voordelen. Zo is het bijvoorbeeld makkelijker om aan een bestaande klant additionele producten te verkopen of kosten te drukken (en zo waarde te verhogen) dan meteen waardevolle klanten binnen te halen. Bovendien hoeven er voor het behouden van klanten geen wervingskosten te worden gemaakt. Aan de andere kant, als een bedrijf voornamelijk behoefte heeft aan grotere klantaantallen, biedt het werven van nieuwe klanten de mogelijkheid om snel de grootte van het klantenbestand uit te breiden.

In dit proefschrift beschrijven we drie studies die gaan over de waardering van bestaande klanten en het vinden van een balans tussen klantbehoud en klantwerving. Elk van deze studies is empirisch getest in de Nederlandse energiemarkt voor consumenten. De liberalisering van deze markt, in 2004, heeft een interessant veld opgeleverd voor marketing onderzoek. Door de enorme toename in concurrentie, is er voor de traditionele spelers in de energiemarkt een grote behoefte ontstaan aan het begrijpen en voorspellen van klantgedrag. Een van deze spelers die al sinds jaar en dag actief is op de Nederlandse markt heeft de drie studies mogelijk gemaakt, zowel door het stellen van vragen, als door het beschikbaar stellen van grote hoeveelheden klantdata.

Het doel van de drie studies in dit proefschrift is het verkrijgen van inzicht in de waarde van klanten in de energiemarkt. In de eerst studie (Hoofdstuk 2) ontwikkelen we een model waarmee de toekomstige waarde van elke klant voorspeld kan worden. Dit model kijkt niet alleen naar bruto marge en retentie, maar neemt ook servicekosten en debiteurenrisico mee als belangrijke waardecomponenten. Door marketingacties te simuleren, kan dit model gebruikt worden voor het vooraf bepalen van het effect van een bepaalde actie op een bepaalde klant. De tweede studie (Hoofdstuk 3) bekijkt het effect van wervingscampagnes op bestaande klanten. In deze studie onderzoeken we of klanten die zich bewust zijn van de scherp geprijsde aanbiedingen voor mensen die nog geen klant zijn, een andere waarde hebben dan mensen die zich niet bewust zijn van deze aanbiedingen. In Hoofdstuk 4 (onze derde studie) richten we ons op het bepalen van het effect van “above-the-line” (ATL, massamediale) en “below-the-line” (BTL, meer persoonlijke) marketinguitgaven op de winstgevendheid van zowel bestaande als nieuwe klanten. Hierbij bestuderen we zowel de onderlinge relatie tussen winstgevendheid van bestaande en van nieuwe klanten, als het effect dat marketinguitgaven hebben op die relatie. Deze drie studies samen dragen bij aan een verhoogd inzicht in de waardering van klanten in de energiemarkt.

BELANGRIJKSTE RESULTATEN

In onze eerste studie (Hoofdstuk 2) hebben we een model ontwikkeld waarmee de toekomstige waarde van elke klant voorspeld kan worden. Dit model kijkt niet alleen naar bruto marge en retentie, maar neemt ook servicekosten en debiteurenrisico mee als belangrijke waardecomponenten. We tonen aan dat, elk van deze componenten noodzakelijk is voor het maken van een goede voorspelling van de waarde van klanten. Vervolgens hebben we dit model gebruikt om het effect van een aantal marketingacties te simuleren. Met een marketingsimulatie wordt voordat een actie daadwerkelijk is uitgevoerd het effect van een bepaalde actie op een bepaalde klant bepaald. Hierbij hebben we gezien dat het niet voldoende is om te kijken naar de waardetoename die gerealiseerd zou kunnen worden als de actie succes heeft; maar dat het ook van essentieel belang is om de kans dat de actie voor een bepaalde klant succes heeft mee te nemen in de uitkomst van de simulatie. Deze combinatie van kans op succes en waarde van succes levert een krachtig instrument op voor het nemen van marketingbeslissingen.

In Hoofdstuk 3 (onze tweede studie) bestuderen we het effect van aantrekkelijk geprijsde wervingsaanbiedingen op de waarde van bestaande klanten. Hierbij hebben we eerst gekeken naar het effect van bewustzijn van de campagne op intentie om klant te blijven en daarna naar de totale waardegevolgen hiervan. Onze studie wijst uit dat klanten die bekend zijn met de wervingsaanbieding een hogere intentie hebben om klant te blijven dan klanten die niet bekend zijn met de aanbieding. Echter, klanten die bekend zijn met de aanbieding zullen ook vaker contact opnemen met het bedrijf om de aanbieding zelf ook te krijgen. Het beleid van het bedrijf hieromtrent is dat een beller de aanbieding ook krijgt, hetgeen resulteert in een lagere bruto marge voor de bellende klant. De verhoogde intentie om klant te blijven voegt niet genoeg toe aan de waarde van de klant om de lagere bruto marge te compenseren. Dientengevolge is de waarde van klanten die zich bewust zijn van de campagne niet significant verschillend van klanten die zich niet bewust zijn van de campagne. Echter, wanneer we niet alleen kijken naar bewustzijn, maar ook de waardering van de aanbieding meenemen, krijgen we een duidelijker beeld. Onze bevinding is dat klanten die de aanbieding aantrekkelijk vinden een hogere intentie hebben om klant te blijven. Zelfs dermate veel hoger dat het effect van een lagere bruto marge hiermee wordt gecompenseerd. Het omgekeerde is waar voor klanten die de aanbieding kennen en deze onaantrekkelijk vinden.

De derde studie (Hoofdstuk 4) behandelt het effect van “above-the-line” (ATL, massamediale) en “below-the-line” (BTL, meer persoonlijke) marketinguitgaven op de winstgevendheid van zowel bestaande als nieuwe klanten. Hierbij bestuderen we zowel de onderlinge relatie tussen winstgevendheid van bestaande en van nieuwe klanten, als het effect dat marketinguitgaven hebben op die relatie. Om deze effecten te kwantificeren, schatten we een “Vector Autoregressive” (VAR) model. Omdat de relatie tussen BTL en winstgevendheid van nieuwe klanten te direct is (hetgeen inherent is aan de wervingsmethodiek), kon het geschatte effect van BTL op winstgevendheid van nieuwe klanten niet worden gemodelleerd. Op basis van dit model concluderen we echter wel dat de “Return on Investment” (ROI) van ATL negatief is, dat wil zeggen, een extra uitgave van 1 miljoen euro resulteert in een extra winstgevendheid van minder dan 1 miljoen euro. Wanneer we kijken naar de relatie tussen de winstgevendheid van nieuwe klanten en de winstgevendheid van bestaande klanten, vinden we dat een hogere winstgevendheid van bestaande klanten leidt tot een lagere winstgevendheid van nieuwe klanten. Echter, het werven van winstgevende klanten leidt tot winstgevendere bestaande klanten.

IMPLICATIES VOOR DE MARKETINGPRAKTIJK

De bevindingen van dit proefschrift zijn niet alleen relevant voor de marketingwetenschap, maar juist ook voor de praktijk. Aangezien alledrie de studies zijn gebaseerd op vragen uit die praktijk, gaan we er vanuit dat onze resultaten voor de managers van dit bedrijf van grote waarde zullen zijn. Van de resultaten van onze eerste studie (Hoofdstuk 2) leren we dat het beeld van de waarde van een klant pas compleet is als er naast retentie en bruto marge ook rekening wordt gehouden met servicekosten en debiteurenrisico. Daarnaast hebben we in deze studie een methode ontwikkeld om de toekomstige waarde van klanten te voorspellen en te simuleren hoe deze waarde beïnvloed kan worden door marketing acties. Met behulp van deze simulaties kunnen we een beste actie per klant bepalen, hetgeen een gerichte marketingbenadering vergemakkelijkt en de winstgevendheid van het klantenbestand verhoogt.

De bevindingen uit Hoofdstuk 3 (onze tweede studie) impliceren dat het effect van wervingscampagnes op bestaande klanten niet zo negatief is als voorheen wel eens werd gedacht. Echter, deze conclusie geldt alleen voor de onderzochte aanbiedingen en generalisaties naar andere aanbiedingen of boodschappen kunnen niet zomaar worden gedaan. Op basis van de waarde-effecten van wervingscampagnes op bestaande klanten, zou het bedrijf wellicht het beleid ten aanzien van klanten die bellen om de aanbieding te krijgen kunnen heroverwegen. Het geven van de aanbieding heeft grote gevolgen voor de bruto marge, wat wellicht niet nodig hoeft te zijn. Tot slot heeft deze studie ertoe geleid dat het mogelijk is om het effect van een grotere groep bewuste klanten of een hogere waardering van een aanbieding te simuleren. Hiermee kan bijvoorbeeld worden bepaald dat wanneer de waardering van de campagne 10% hoger is, dit tot een substantieel hogere waarde van het klantenbestand leidt. Dergelijke simulaties kunnen worden gebruikt ten aanzien van het uitrollen van toekomstige wervingscampagnes.

Onze derde studie (Hoofdstuk 4) heeft ons laten zien hoe de relatie tussen de winstgevendheid van nieuwe klanten en bestaande klanten wordt beïnvloed door marketingcampagnes. Dit inzicht biedt een middel om te kijken wat het effect is van een extra investering in ATL op de winstgevendheid. In onze studie vinden we dat een extra investering in ATL leidt tot hogere winstgevendheid, maar niet zo hoog als de investering in ATL zelf. Managers kunnen dit inzicht wellicht gebruiken om hun budgetten anders in te zetten. Hierbij is het verstandig om niet alleen te kijken naar de totale winstgevendheid van nieuwe klanten, maar ook naar de onderliggende aantallen nieuwe klanten en de winstgevendheid per nieuwe klant. Idem dito voor bestaande klanten. We leren uit onze studie dat ATL alleen effectief is voor het behouden van klanten. Het zou interessant zijn om te onderzoeken of de inhoud van ATL campagnes (wel of geen aanbod) van invloed is op de winstgevendheid per behouden klant.

Al met al hebben de drie gedane studies ons veel inzicht gegeven in klantwaarde-vraagstukken in de energiemarkt. We hopen dat de gevonden antwoorden zowel voor de marketingwetenschap als voor de marketingpraktijk van toegevoegde waarde zullen zijn.