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RETURN ON MARKETING INVESTMENTS IN B2B CUSTOMER RELATIONSHIPS:

A DECISION-MAKING AND OPTIMIZATION APPROACH

Sandra Streukens (Corresponding Author)

Department of Business Studies, Hasselt University

Agoralaan – Building D

BE-3590 Diepenbeek, Belgium

T: +32 11 26 8628

E: sandra.streukens@uhasselt.be

Stan van Hoesel

Department of Quantitative Economics, Maastricht University

PO Box 616, 6200 MD Maastricht, The Netherlands

T: +31 43 3883727

E: s.vanhoesel@ke.unimaas.nl

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Sandra Streukens is currently an assistant professor of marketing with the Department of Business Studies at Hasselt University (Belgium). Her main research interests include services marketing, research methodology, service employee management, and return on services. Her work is published in international journals like *Marketing Letters*, *Journal of Economic Psychology*, *Journal of Business Research*, *Industrial Marketing Management*, *Information and Management*, *Managing Service Quality*, and *International Journal of Service Industry Management*.

Stan van Hoesel is professor of operations research with the Department of Quantitative Economics at Maastricht University (The Netherlands). His main research interests include network design, frequency assignment, and combinatorial optimization. His work is published in international journals like *Management Science*, *European Journal of Operations Research*, *Transportation Science*, *International Journal of Production Economics*, and *Mathematical Programming*.

ABSTRACT

The basic notion of relationship marketing entails that firms should strive for *mutually* beneficial customer relationships. By combine relationship marketing theory and operations research methods, this paper aims to develop and demonstrate a managerial decision-making model that business market managers can use to optimize and evaluate marketing investments in both a customer oriented and economically feasible manner.

The intended contributions of our work are as follows. First, we add to the return on marketing literature by providing a first decision-making approach that explicitly assesses the optimization of marketing investments in terms of profitability, effort, and resource allocation. Second, we show how the risk of marketing investments can be assessed by means of sensitivity analysis. By means of an empirical study we demonstrate the versatility of our decision-making approach by assessing various critical decision making issues for business marketing managers in detail. Furthermore, we show how our decision-making approach can be a valuable extension of commonly used customer satisfaction studies.

Keywords: Return on Marketing, Relationship Marketing, Optimization, Marketing Decision Making

1. INTRODUCTION

Consistent with the basic tenet of relationship marketing that a company should strive for *mutually* beneficial customer relationship (LaPlaca, 2004) there is a strong need for managerial decision-making models that combine marketing theory with mathematical rigor (Metters & Maruchek, 2007; Brettbauer, 2004; Boudreau, Hopp, McClain, & Thomas, 2003).

Recent work in business marketing management underscores this premise of uniting soft customer perceptions and hard objective measures in a single decision-making tool. For instance, Gök (2008) demonstrates the need for and value of including forward-looking customer evaluative judgments like satisfaction in marketing performance evaluation. Furthermore, Seggie, Cavusgil, and Phelan (2007) underscore the need for linking marketing initiatives to quantifiable financial outcomes. Nevertheless, models that combine marketing theory and financial performance measures to guide marketing investment decision making are scant in the literature. Therefore, the aim of our study is to develop and demonstrate a practical and versatile decision-making approach that assists business market managers in evaluating and optimizing marketing investments in an economically justified, yet customer-oriented manner.

In line with the aforementioned need for decision-making models that combine marketing theory with mathematical rigor the two main building blocks of our decision-making model include relationship marketing theory and operations research techniques. Anchoring the model in operations research principles permits decision makers to balance marketing revenues and costs. The use of relationship marketing theory to conceptualize different elements in the decision-making model allows for customer-oriented decision making. With this study we contribute to the literature in the following ways. First, compared to existing models (e.g., Rust et al. 1995; 2004) our approach adds to the return on marketing literature by explicitly

optimizing marketing investment profitability both in terms effort level as well as effort allocation. Second, we show how investment risk can be assessed by examining the robustness of the model's projected financial consequences.

The remainder of this paper is structured as follows. Section two focuses on the theoretical development of our decision-making approach. We start this first section by providing an overview of our decision-making model. Subsequently, we provide a detailed explanation of the various elements and links in our decision-making approach. Section three of this paper summarizes the empirical study conducted to calibrate the customer relationship part, or more precisely the marketing investment revenues component, of our approach. Building on the results of this empirical study, the fourth section shows how our model can be used to tackle critical decision-making issues such as optimizing marketing investment profitability, optimizing marketing investment effort allocation and assessing marketing investment risk. In the fifth and sixth section, we respectively discuss the various implications for business market managers and explain how our optimization approach can be extended to accommodate situations other than the one illustrated in this paper.

2. MODEL DEVELOPMENT

We start this section with a general overview of the main components of our decision-making model and their interrelationships. Subsequently, the different components are specified into detail.

2.1 Overview of the decision-making approach

In line with the basis of relationship marketing, the starting point of our decision-making approach is that customer-firm relationships should be *mutually* beneficial (see also LaPlaca, 2004). In terms of marketing investments, the idea of mutually beneficial customer-firm relationships is reflected in the return on marketing approach (see also Rust, Zahorik, & Keiningham, 1995) proposing that marketing investments should improve a firm's financial performance via improvements in customer evaluative judgments. Consequently, an effective decision-making model guiding marketing investments should thus carefully and explicitly balance changes in customer's perceptions stemming from marketing investments and the firm's financial consequences of these marketing investments.

To arrive at a decision-making approach to evaluate and optimize marketing investments that contribute to the establishment of mutual beneficial relationships, the following two elements are of crucial importance. First, in line with Zhu, Sivakumar and Parasuraman (2004) our decision-making framework explicitly takes into account both the involved marketing investment revenues and costs, thereby allowing the firm to conduct an economically justified analysis of marketing investments. Second, changes in customer evaluative judgments resulting from marketing investments should be explicitly connected to financial consequences. For this, we draw upon relationship marketing theory to model the marketing investment revenues in our approach. Figure 1 below graphically presents the main elements of our decision-making approach and shows their interrelationships.

INSERT FIGURE 1 ABOUT HERE PLEASE

The first link (i.e., Link 1) in F

Figure 1 represents the positive relationship between the revenues stemming from marketing investments and the associated profitability of these investments. In line with the so-called expected value approach, which has been widely applied in finance and accounting and recent work in customer equity modeling (see Kumar & George, 2007), our decision-making approach models the revenues associated with a particular marketing investment as the product of a customer's retention probability and monetary value which is subsequently summed over the firm's customers. Pursuing an expected value approach to model marketing investment revenues offers the following opportunities. First, the use of predictive response modeling to assess the probability that customers remain loyal over a given period offers a rich opportunity to incorporate key relationship marketing constructs into the calculation of marketing investment revenues and profitability. Second and synergistically, integrating customer relationship perceptions in the marketing investment revenues / profitability calculation ensures the development of truly customer-oriented marketing investments strategies. In specifying the process underlying the generation of marketing investment revenues related to Link 1 in Figure 1, we heavily draw upon relationship marketing theory (see also the rectangle denoted "relationship marketing theory" in Figure 1).

The profitability consequences of marketing investment costs or effort are reflected by Links 2 and 3 in Figure 1. Two separate links are needed to adequately capture the profitability consequences of these costs as they have a dual effect on profitability. First, as reflected by Link 2, marketing investment costs have an indirect positive influence on profitability via the customer evaluative judgments they aim to improve. Second, as reflected by Link 3, marketing investment costs have a direct negative impact on investment profitability. To model Links 2 and 3 we make use of decision calculus methodology.

The remainder of this section explains the various elements presented in Figure 1, captures them in mathematical equations, and brings the elements together in a mathematical framework that can be used to evaluate and optimize marketing investments.

2.2 Modeling marketing investment revenues

This paragraph focuses on modeling the marketing investment revenues function and the integration of this function in our decision-making model. First we explain the role of relationship marketing theory in modeling the marketing investment revenues function. Second, we show how the resulting revenues function can be incorporated in our mathematical decision-making model to evaluate and optimize marketing investment decisions.

As outlined above and depicted in Figure 1, the probability that a customer is retained over a certain time period by the company plays a crucial role in determining marketing investment revenues (and thus ultimately marketing investment profitability). Consequently, understanding what drives this customer retention probability is necessary to develop profitable marketing initiatives. To understand the customer's retention probability in business settings the beliefs -> attitude -> behavioral intent model offers a valuable conceptual model (Lewin, 2008; Lam, Shankar, Erramilli, & Murthy, 2004).

Building on the general structure of the beliefs -> attitude -> behavioral intent model we used the following constructs in modeling the marketing investment revenues function. In explaining customer attitudes and behavior, perceived quality and perceived value are considered the two most important beliefs (Cronin, Brady, & Hult, 2000). Perceived quality is the consumers' cognition-based appraisal of an offerings overall excellence or superiority (Zeithaml, 1988). Perceived value captures the customer's trade-off between sacrifices and returns involved

in using a particular market offering (Cronin et al., 2000). Two key attitudinal constructs that play a role in the formation of customer loyalty are satisfaction and trust (Selnes, 1998; Garbarino & Johnson, 1999). Satisfaction is the customers' cumulative evaluation that is based on all experiences with the company's offering over time (Anderson, Fornell, & Lehmann, 1994). Trust is the customer's confidence that the seller can be relied on to deliver according to their promises (Nijssen, Singh, Sirdeshmukh, & Holzmueller, 2003). Finally, following common practice in customer research, we use behavioral intentions as a proxy for customer loyalty. Customer loyalty is a buyer's overall attachment to an offering, brand, or organization (Oliver, 1999). Moreover, similar to other return on marketing models, this study conceptualizes customer loyalty as the probability of securing the customers' monetary value over a specific time period (Rust, Lemon, & Zeithaml, 2004). Table 1 summarizes the key literature regarding the relationships among the various belief, attitude, and intent constructs defined above.

INSERT TABLE 1 ABOUT HERE PLEASE

In addition to understanding how customer evaluative judgments relate to marketing investment revenues, we need to integrate the set of relationships connecting customer beliefs, attitudes, and behavioral intent into a formal marketing investment decision-making approach. To achieve this we proceed as follows.

Maintaining with the notion of a chain of effects between beliefs, attitudes, and behavioral intentions, investments aimed at improving customer quality perceptions (i.e., beliefs) are assumed to eventually trigger an increase in customer retention probability. Or analogous to

Rust et al.'s (2004) return on marketing terminology, customer quality perceptions are retention probability drivers. Without loss of generality, the remainder of this paper focuses on the financial consequences of marketing investments aimed at improving customer quality perceptions. These drivers (i.e, quality perceptions) are denoted as $y_i (i \in I)$.

Building on the nomological network connecting quality perceptions to customer retention, the impact of changes in the various drivers $y_i (i \in I)$ due to targeted marketing investments positively influences customer retention rates and thus eventually marketing investment revenues. The overall influence of changes in the various drivers on the customer's retention probability can be summarized by function f_{y_i, loy_c} . As will be shown in section four of this paper, function f_{y_i, loy_c} can be determined directly from empirical analysis of the set of hypothesized relationships among the different customer constructs linking customer quality perceptions to customer retention.

To ultimately determine the marketing investment revenues, the customer retention probability is to be multiplied by the amount of customer monetary value that a customer is likely to generate over a specific time period and summed over all the relevant customers. Mathematically, this is expressed in Equations (1a) and (1b) below.

$$REV = \sum_{c=1}^c [(loy_c CMV_c) - (loy(0)_c CMV(0)_c)] \quad (1a)$$

Where

$$loy_c = \sum_{i \in I} f_{y_i, loy_c} y_i \quad (1b)$$

In Equation (1a) the term loy_c refers to the customer retention probability as a result of some particular marketing investment, whereas the term $loy(0)_c$ is the status quo customer retention probability and refers to the customer retention probability before the implementation of the marketing initiative aimed at increasing customer retention. Furthermore, the terms $CMV(0)_c$ and CMV_c refer to the customer monetary value before and after the marketing investment, respectively. Thus, Equation (1a) implies that marketing investment revenues are the difference between the current customer revenues (associated with the current level of customer evaluative judgments) and the revenues that can be expected when marketing investment aimed at influencing customer evaluative judgments are made. In Equation (1b) the term f_{y_i,loy_c} denotes the impact of the different drivers y_i on the customer's probability to remain loyal over some time period as reflected by the nomological network of relationships connecting quality perceptions to customer retention probability (see also rectangle named "relationship marketing theory" in Figure 1).

2.3 Modeling marketing investment costs

As reflected by Links 2 and 3 in Figure 1, marketing investment costs or effort have both a direct negative and an indirect positive effect on marketing investment profitability. The indirect positive effect stems from the fact that targeted marketing investments (denoted by eff_i) influence customers' quality perceptions (y_i), which through increased loyalty, yield marketing investment revenues (see also Link 2 in Figure 1). Thus, the quantification of this particular positive relation between investment effort (eff_i) and the level of the drivers (y_i) is crucial to the development of our decision making model. We use the response curve proposed in Little's

(1970) ADBUDG function to estimate this relationship. The value of Little's (1970) ADBUDG model is two-fold. First of all, ADBUDG offers a “simple, robust, easy to control, adaptive, as complete as possible, and easy to communicate with” (Little, 1970 p.466) modeling approach. Second, as the parameters of the model are calibrated in consultation with managers, the ADBUDG model reflects Blattberg and Hoch's (1990) notion that decision quality is best when both statistical and human input is combined. In general terms, the ADBUDG function is defined as shown in Equation (2).

$$y_i = a_i + (b_i - a_i) \frac{eff_i^{c_i}}{d_i + eff_i^{c_i}} \quad (2)$$

Concerning Equation (2), parameters a_i and b_i restrict driver y_i to a meaningful range (i.e., $[a_i, b_i]$). More specifically, a_i represents the level of driver i (i.e., y_i) when no marketing investments are made for this variable (i.e., $eff_i = 0$); b_i corresponds to the value of the driver when an infinite amount of resources would be invested in this driver (i.e., $eff_i \rightarrow \infty$).

Parameters c_i and d_i determine the shape of the relationship between y_i and eff_i . More specifically, parameter c_i allows the response curve to be either concave or s-shaped, whereas parameter d_i reflects the slope of the response curve.

Calibration of the ADBUDG function shown in Equation (2) automatically provides an estimate of the total level of investment costs, which has a direct negative impact on the profitability of marketing investments (see also Link 3 in Figure 1). The total level of marketing investment costs equals the amounts invested in the different specific drivers summed over all relevant drivers. Thus, as eff_i reflects the investment effort needed to influence a

particular customer retention driver y_i , the total investment effort associated with a particular investment strategy aimed at improving a set of drivers can be defined as:

$$\text{Total efforts} = \sum_{i \in I} (eff_i - eff(0)_i) \quad (3)$$

In Equation (3) the term $eff(0)_i$ in the investment level needed to maintain the $y(0)_i$ level of the drivers (please note that this relationship is implied by Equation (2)). The $y(0)_i$ levels of the drivers correspond with the $loy(0)_c$ parameter in Equation (1a). As indicated by Link 3 of our conceptual model in Figure 1, the level of total invest effort directly reduces the profitability of marketing investments.

2.4 Modeling and optimizing marketing investment profitability

The profitability of marketing investments equals the difference between the revenues and costs associated with a particular marketing investment. Consequently, the profitability function, presented in Equation (4), follows directly from the revenue and total investment effort function expressed in Equations (1a) and (3) respectively.

$$profits = \left[\sum_{c=1}^C [(loy_c CMV_c) - (loy(0)_c CMV(0)_c)] \right] - \left[\sum_{i \in I} [eff_i - eff(0)_i] \right] \quad (4)$$

Similar to the work of Rust et al. (1995, 2004) Equation (4) yields sufficient information to make marketing investments financially accountable and to compare and evaluate them vis-à-vis alternative (marketing) investment opportunities. In addition to making marketing investments financially accountable, optimizing marketing investment profitability is an issue of great managerial interest (Zeithaml, 2000) which so far has received little attention in the existing literature.

In order to devise marketing investment strategies that maximize profitability, the expression presented in Equation (4) serves as an objective function in an optimization problem. The core of this optimization problem is to maximize marketing investment profitability by finding optimal spending levels eff_i for the different drivers y_i . Or equivalently, determining which spending levels eff_i yield optimal levels of customer perceptions regarding the different drivers y_i as reflected by a maximum level of marketing investment profitability.

Building on the interrelationships among marketing investment profitability, revenues, and costs (see also Figure 1), maximizing the profitability function is subject to the following constraints. The first constraint, presented below in Equation (5a) models the impact of changes in the input variables y_i on the retention probability as hypothesized by the set of relationships underlying the loyalty formation process (see also rectangle “Relationship Marketing Theory” in Figure 1).

$$loy_c = \sum_{i \in I} f_{y_i, loy_c} y_i \quad (5a)$$

The second constraint models the effect of investment effort eff_i on the level of the input variables y_i following Little’s (1970) ADBUDG function. As a reminder, this constraint is modeled as follows (see also Equation (2)).

$$y_i = a_i (b_i - a_i) \frac{eff_i^{c_i}}{d_i + eff_i^{c_i}} \quad (5b)$$

Third, we impose a budget constraint implying that the total investment effort cannot exceed a pre-set budget B . This budget constraint is summarized in Equation (5c).

$$\sum_{i \in I} (eff_i - eff(0)_i) \leq B \quad (5c)$$

Finally, we impose a nonnegativity constraint for eff_i , which is formally expressed in Equation (5d).

$$eff_i - eff(0)_i \geq 0 \quad (5d)$$

Together the objective function and constraints described above yield the optimization framework presented in Exhibit 1.

Exhibit 1: Overview of the decision-making / optimization framework

max	$\left[\sum_{c=1}^C [(loy_c CMV_c) - (loy(0)_c CMV(0)_c)] \right]$	-	$\sum_{i \in I} [eff_i - eff(0)_i]$	
s.t.	loy_c	=	$\sum_{i \in I} [f_{y_i, loy_c} y_i]$	$\forall_{i \in I}$
	y_i	=	$a_i + (b_i - a_i) \frac{eff_i^{c_i}}{d_i + eff_i^{c_i}}$	$\forall_{i \in I}$
	$\sum_{i \in I} (eff_i - eff(0)_i)$	\leq	B	$\forall_{i \in I}$
	$eff_i - eff(0)_i$	\geq	0	$\forall_{i \in I}$

In the following two sections we will estimate and calibrate the various parameters required to implement the decision-making or optimization model. To begin with, section three describes the empirical study conducted to understand and model the marketing investment revenues function consisting of the customer's retention probability and the customer monetary value (see also Equations (1a) and (1b)). Section four uses the results of the empirical study to demonstrate the various possibilities our optimization framework in Exhibit 1 offers for marketing decision making.

3. ANALYZING CUSTOMER RETENTION AND CUSTOMER MONETARY VALUE

3.1 Sampling

Survey data needed to estimate the different elements of the marketing investment revenues function (see also Figure 1 and Equations (1a) and (1b)) were obtained from business customers of the supplies business unit of a large international operating manufacturer of office equipment. This business unit sells the supplies (e.g. paper and toner) needed to operate their office equipment (copiers and printers). Furthermore, the company aims to build long-term relationship with its customers based on service excellence. The population of this study consists of B2B customers for which it is economically infeasible to pursue a one-to-one marketing strategy. Overall, these customers make up approximately 37.6 % of the total customer base.

In total, we obtained an effective response rate of 36.6 % or 183 respondents. Examination of the sample profile led to the conclusion that our sample is representative of the underlying target population. Furthermore, all questionnaires were labeled with the customers' unique ID-code enabling us to link the customer's perceptual and (objective) sales data.

3.2 Data

All respondents that participated in our study received a questionnaire containing items on perceived quality, overall satisfaction, perceived value, trust, and behavioral intentions. Perceived quality was measured by means of 7 attributes that covered the most important product and service aspects from the customers' point of view (cf. Rust et al. 1995). Overall cumulative satisfaction was measured by means of a single item (Anderson et al., 1994). Perceived value (4

items) was assessed using a scale that was adapted from the measurement instruments developed by Dodds, Monroe, and Grewal (1991) and Cronin et al. (2000). Trust (5 items) was measured by means of the scale developed by Kumar, Scheer and Steenkamp (1995). All above-mentioned constructs were measured on 11-point Likert scales. The customer's retention probability was assessed by measuring the current percentage spent at the company under study relative to the total amount of money spent at the particular product category (Rust et al., 2004). See Table 2 for an overview of the descriptive statistics of the customer constructs assessed for this study. Moreover, Table 5 accompanying the application of our decision-making model contains a short description of each quality item or driver.

Finally, data on customer sales over an 18 month period were obtained from the company's data base. To account for customer differences in purchase times, monthly sales were summed over a three month's time period.

INSERT TABLE 2 ABOUT HERE PLEASE

3.3 Estimation procedure customer retention probability

To estimate the relationships explaining the customer's retention probability, we opted for PLS path modeling (SmartPLS2.0 M3) as our model contains both formative and reflective scales.

To restrict the (predicted) retention probabilities to a feasible 0-1 range, all stated retention probabilities underwent a logit transformation. To our best knowledge no PLS path modeling software is available to accommodate the resulting non-linear logit curve. To

overcome this problem we proceeded as follows. Based on the retention probability we determined each respondent's odds ratio. Subsequently, taking the natural logarithm of the odds ratio and specifying it as a formative indicator for the loyalty construct allowed us to estimate it as linear function of its hypothesized antecedents.

To evaluate the statistical significance of the various parameter estimates we construct bias-corrected bootstrap percentile confidence intervals based on 5,000 bootstrap samples.

3.4 Estimation procedure customer monetary value

In line with Venkatesan and Kumar (2004) customer monetary value (CMV_c) is modeled as a function of past behavior and customer characteristics such as customer size, customer type, and relationship length. The following issues warrant specific attention when analyzing panel data. First, to accommodate the problem of endogeneity due to the use of lagged dependent variables which are needed to examine the effect of past behavior, we used the first difference specification of customer monetary value ($\Delta CMV_{c,t} = CMV_{c,t} - CMV_{c,t-1}$) as the dependent variable in our model and $CMV_{c,t-2}$ as an independent variable (Baltagi 2008, p.148). Second, to examine whether a one-way or two-way error component random effects¹ model is most appropriate a series of Breusch-Pagan need to be conducted (Wooldridge, 2002). The dynamic regression model for the situation at hand is summarized in Equation (6)

$$\begin{aligned} \Delta CMV_{c,t} = & + \gamma_1 CMV_{c,t-2} + \gamma_2 QUAN_{c,t-1} + \gamma_3 SIZE1_c + \gamma_4 SIZE2_c \\ & + \gamma_5 TYP1_c + \gamma_6 TYP2_c + \gamma_7 REL_c + \varepsilon_{i,t} \end{aligned} \quad (6)$$

¹ A fixed effects panel data model was not feasible as all regressors except the lagged dependent variable are time constant.

Where $QUAN_{c,t-1}$ refers to the quantity purchased in US dollars by the customer in period $t - 1$, $SIZE1_c$ and $SIZE2_c$ are dummies reflecting the size of the customer expressed in past sales volume (entire population is split into four groups based on quartiles, only the lowest three quartiles were included in our sampling frame), $TYPE1_c$ and $TYPE2_c$ are dummies reflecting the product line(s) the customer uses. All four dummy variables can be considered time-invariant. The variable REL_c denotes the length of customer's relationship with company measured in days since the first purchase. The variables $\Delta CMV_{c,t}$ and $CMV_{c,t-2}$ are as defined above. To estimate the dynamic regression model expressed in Equation (6) we used SAS v9.2's PROC PANEL.

3.5 Empirical results customer retention probability

We begin with evaluating the psychometric properties of the various scales used to tap customer evaluative judgments. In assessing the performance of the scales used in this study it is important to distinguish between (multiple-item) reflective and formative scales (MacKenzie, Podsakoff, & Jarvis, 2005). In this study, perceived value and trust are considered reflective scales, whereas perceived quality is considered a formative scale.

Concerning the reflective scales, unidimensionality is evidenced by the fact that the first eigenvalue matrix of the respective item correlation matrices exceeds one, whereas the other eigenvalues are less than one (Tenenhaus, Esposito Vinzi, Chatelin, & Lauro, 2005). Furthermore, reliability was evidenced as for both reflective scales the internal consistency statistic passed the 0.70 cut-off value. Support for the reflective scales' within-method convergent validity is provided by the high average variance extracted levels and the magnitude and significance of the indicator loadings.

Regarding formative scales the most relevant type of validity is content validity (Diamantopoulos & Winklhofer, 1999). The fact that we designed the scale assessing perceived quality scale to encompass all relevant business processes together with the significant loadings provides substantial evidence for the content validity of this formative scale.

Finally, for all scales used in this study discriminant validity was evidenced as all between-construct correlation coefficients significantly differ from an absolute value of 1. See Table 2 for the relevant figures regarding the evaluation of the scales' psychometric properties.

Turning to the empirical results for the hypothesized structural relationships underlying the revenue generating process, which are presented below in Table 3, the bootstrapped \bar{R}^2 confidence intervals indicate that the theoretical model has a good fit to the data. Furthermore, as indicated by the statistical significance for the majority of the regression coefficients it can be concluded that also in B2B settings managing customer attitudes and perceptions is vital in creating customer loyalty. Thus, as evidenced by the chain of effects connecting customer beliefs and attitudes to customer behavior, directing investment effort at improving customer beliefs such as perceived quality offers an important opportunity to make customers more loyal. Put differently, marketing investments aimed at improving customer evaluative judgments are an effective way to enhance revenues.

INSERT TABLE 3 ABOUT HERE PLEASE

Despite the insights to manage customer loyalty among business customers, these empirical results alone are insufficient to resolve important management issues such as the optimal amount and optimal allocation of investment efforts needed to improve customer

evaluative judgments in an economically justified way. This underscores the need for a formal decision-making approach to evaluate and manage marketing investments even further.

3.6 Empirical results customer monetary value

Comparing the results for the Breusch-Pagan test for both a one-way and two-way error component random effects model showed that a one-way error component random effects model is appropriate for the situation at hand ($\Delta\chi^2(1) = 1.00$). Furthermore, as evidenced by the R^2 value of 0.54 our model shows a good fit to the data. The estimation results for the various parameters in our dynamic regression model are presented below in Table 4.

INSERT TABLE 4 ABOUT HERE PLEASE

The results in Table 4 demonstrate that past customer monetary value, past purchase quantity, and customer size are important indicators of future customer monetary value.

Building on the empirical results providing insight into the customer loyalty formation process and customer monetary value (i.e. key elements of the marketing investment revenues component of our model), section four focuses on how these empirical results can be used to put our marketing investment decision-making approach into practice.

4. APPLICATION OF THE DECISION-MAKING APPROACH

This section demonstrates how our decision-making approach presented in Exhibit 1 can assist business market managers in tackling the following vital marketing investment issues: what is the optimal level of marketing investment effort to maximize profitability, what is the

projected return on investment for a specific investment initiative, how should we optimally allocate the investment efforts over the drivers, and how risky is the projected investment strategy.

Before we can assess these issues, we first need to calibrate the functions pertaining to marketing investment revenues (i.e. Link 1 in Figure 1) as well as the indirect positive and direct negative effect of investment effort on investment profitability (i.e. respectively Links 2 and 3 in Figure 1). Please note that additional detailed background information on the calibration of the model components can be found in the appendices to this paper.

4.1 Calibrating the investment revenues function

The impact of each driver y_i on the customer's retention probability, and thus ultimately marketing investment revenues and profitability, as reflected by f_{y_i,loy_c} , can be calculated directly from the empirical data presented in Tables 2 and 3 as follows. Given that the model describing the revenue generating process is non-recursive (acyclic), the total influence of each input variable y_i on loy_c is summarized below in Equation (7) and will be referred to as λ_{y_i,loy_c} in the remainder of this paper.

$$f_{y_i,loy_c} = \lambda_{y_i,loy_c} = \sum_{P:(y_i \rightarrow loy_c)} \left(\prod_{(y_i, loy_c) \in P} w_{ij} \right) \quad (7)$$

In Equation (7) w_{ij} are the different marginal effects of the relevant independent variables on the relevant dependent variables as hypothesized in our relationship marketing theory model (see also Figure 1). In words, Equation (7) states that the effect of a unit change in driver y_i on the customer's retention probability loy_c can be computed by calculating the product of the

coefficients w_{ij} belonging to each of the separate relationships connecting y_i and loy_c , and subsequently summing these products over all relevant paths connecting y_i and loy_c .

It is important to note that the computation of the marginal effects w_{ij} depends on the functional form of the equations describing the various links in the structural model connecting y_i and loy_c . For relationships characterized by a linear functional form w_{ij} equals the relevant unstandardized regression coefficient. For the logit equation with loy_c as dependent

variable, w_{ij} is computed as $w_{ij} * \frac{e^{-(a+w_{1j}x_1+w_{2j}x_2+\dots+w_{kj}x_k)}}{(1+e^{-(a+w_{1j}x_1+w_{2j}x_2+\dots+w_{kj}x_k)})^2}$ where the w_{ij} -parameters are the

relevant unstandardized coefficients belonging to the k independent variables. All needed unstandardized regression coefficients result from our empirical study (see also Tables 2 and 3). Following the idea expressed in Equation (7), Table 5 summarizes the average influence of a one-unit change in y_i on a customer retention probability loy_c for the situation at hand.

The dynamic regression results presented in Table 4 are used to predict the customer monetary value over the next time period (quarter). Together the customer retention probability as a function of drivers y_i and the estimates for each customer's monetary value provide the necessary information to model the customer revenues function reflected by Equation (1a).

4.2 Calibrating the investment effort functions

To capture the profitability consequences of the marketing investment costs the ADBUDG based function expressed by Equation (2) needs to be calibrated. It should be noted that once we calibrated this function for each of the drivers (i.e., quality elements) we automatically have an estimate for the total investment effort as reflected by Equation (3). To

calibrate the function between investment effort (eff_i) and drivers (y_i) as captured by Equation (2), we first need to understand what actions are capable of influencing the customer's perceptions regarding these drivers. Interviews with the company's customer service managers and several customers yielded insight in this matter. Second, we need to assess how various levels of these actions, reflecting different investment effort levels, relate to changes in the customer's perceptions of the various drivers (i.e., rating shifts). As shown in Appendix 1 a set of standard questions is asked to determine the shape of the function (i.e., ADBUDG parameters c_i and d_i) between investment effort and the driver perceptions (see also the original work of Little (1970) or the more recent application of Dong, Swain, and Berger (2007)).

For reasons of confidentiality we use an example cost-function in the current application of our decision-making model. As each practical application of our model is likely to have a unique cost-function reflecting the idiosyncrasies of each setting, the use of an example cost-function does not limit the applicability of our model. Regarding the current application, parameter c_i was set to 1, thereby reflecting that the investments aimed improving customers' quality perceptions are subject to diminishing returns (Little, 1970). For parameter d_i a value of \$50,000 was chosen to approximate the underlying cost function. Finally, as the purpose of parameters a_i and b_i is to restrict changes in y_i to a meaningful range, these parameters are implicitly determined by the endpoints of the scales we used to measure the customer's perceptions concerning the various drivers. Consequently, parameter a_i is set to 1 (the lowest value of the measurement scale used) and parameter b_i is set to 11 (the highest value of the measurement scale used).

4.3 Investment strategy

Rust, Moorman, and Dickson (2002) conclude that financial returns on marketing investments can arise from increasing revenue by increasing satisfaction, decreasing costs, or both. Furthermore, investment profitability may vary as a function of retaining current customers and/or gaining new customers (Rust et al. 2004). Although many investment strategies are possible and no company can afford to ignore both customer acquisition and cost reduction in favor of respectively customer retention and revenues, the current application demonstrates the optimization of marketing investment profitability as a result of increasing in revenues due to enhanced customer retention. This choice is based on Rust et al. (2002) who show that revenues expansion due to increased satisfaction yields superior results over cost reduction strategies. Furthermore, the work of Fornell and Wernerfelt (1987, 1988) evidences that customer retention is an economically more feasible strategy than customer acquisition. Despite the focus on revenues expansion through customer retention, section six of this paper later elaborates how our optimization framework can be adapted to accommodate other situations such as designing optimal investment strategies for both customer retention and acquisition.

Below we outline the results regarding the application of our decision-making model. The software package AIMMS² was used to perform all optimization analyses. More specifically we opted for a subgradient optimization method. Furthermore, in demonstrating the applicability of our optimization framework two alternative situations are presented. First, no limit is assumed on available investment resources, that is, the budget restriction is relaxed. Second, we will demonstrate the use of our decision-making approach in situations where there is a budget

² AIMMS stands for Advanced Interactive Mathematical Modeling Software for more information see also www.aimms.com and Appendix 1 to this paper.

constraint. Overall, the use of our decision-making framework will proceed in exact the same manner regardless of whether a budget constraint is imposed or not.

4.4 Optimal level of investment effort

Coherent with Rust et al.'s (1995) idea that marketing investments should be optimized rather than maximized, the concave relationship between investment effort and investment profitability for the current application presented in Figure 2 further underscores the need to carefully balance costs and revenues when evaluating marketing investments. Put differently, Figure 2 illustrates that it is possible to over-invest in marketing initiatives in terms of profitability and that an optimum investment level yielding a maximum investment profitability exists.

INSERT FIGURE 2 ABOUT HERE PLEASE

Our decision model can be used as follows to determine this optimum investment level. Analytically, the optimum investment level follows from the derivative of our profit function. In general, marketing investments remain economically feasible as long as the derivative of the profit function is larger or equal to zero. The optimal level of investment level is reached when this derivative equals zero. Setting the derivative of the profit function equal to zero and solving this equation for the situation at hand, shows that an optimal investment level of \$42,000 yields a maximum investment profitability level of \$8,894.

It should be stressed that our decision-making model is not restricted to finding a maximum level of marketing investment profitability in situations were the amount of available

investment resources is unlimited (i.e. no budget restriction applies). To further illustrate the versatility of our decision-making model we subsequently assume that a business market manager has a limited budget of \$10,000 available for making marketing investments. Our approach also is suitable for addressing the issue of how to get the most out of this restricted amount of resources. Running our optimization model with the budget constraint set to \$ 10,000 points out that this budget can lead to a maximum marketing investment profitability level of \$4,480.

As our decision-making approach clearly and directly provides estimates of the level of investment effort needed to realize a certain level of profitability, the rate of return of investment³ (*ROI*) can be computed as shown in Equation (8).

$$ROI = \left(\frac{profits - tot.effort}{tot.effort} \right) * 100\% \quad (8)$$

Using Equation (8) shows that the rates of return on investment are 21.18% and 44.80% for the situation without (i.e., investment level of \$42,000) and with (i.e., investment level of \$10,000) a budget constraint respectively.

In addition to determining the optimal level of investment effort, an optimal allocation of this investment effort is equally important in maximizing investment profitability (Mantrala, Sinha, and Zoltners, 1992).

4.5 Optimal allocation of investment effort

³ Please note that the formula to assess the rate of return on investment does not exclude the use of more advanced calculations such as including the discounted residual value or using the discounted value of the cash flow in determining the rate of return. We would like to thank one of the reviewers for bringing this to our attention.

In determining the optimal allocation of the investment budget over the various drivers, the (derivative of the) profit function plays again a crucial role. In particular, the optimal allocation of investment effort $\sum_{i \in I} (eff_i - eff(0)_i)$ over the different drivers y_i is determined by the absolute and relative magnitude of the partial derivatives of the profit function with respect to various effort levels eff_i needed to improve the different drivers.

In general terms our model determines the optimal allocation of the available investment budget effort as follows. Any optimal allocation starts with assigning all available investment effort to the driver for which the partial derivative of the profit function with respect to investment effort eff_i is highest, say driver p . Eventually each partial derivative decreases, reflecting diminishing returns on investment. As such, the partial derivative with respect to eff_p at some stage will equal the partial derivative with respect to eff_q . Here driver q is the driver for which the partial derivative of the profit function with respect to effort is overall second highest. Upon reaching this equilibrium of partial derivatives, the optimal allocation is maintained by dividing the remaining available investment effort over both drivers p and q in such proportions that the partial derivatives of the drivers remain equal. This proportion depends on the ADBUDG parameters a_i, b_i, c_i , and d_i , and the impact of each driver on investment profitability, λ_{y_i, loy_e} . This process of comparing the profit function's partial derivatives belonging to the different drivers continues until the entire budget is spent.

For the situation at hand we now demonstrate how the optimal investment level determined previously needs to be allocated to indeed achieve the maximum level of investment profitability. To do this we again run the optimization framework presented in Exhibit 1, setting the budget constraint equal to \$42,000 (i.e., optimal investment effort level). The results of this

analysis are presented in Table 5. Likewise, we determined the optimal allocation of resources for the situation in which there is only a limited budget of \$10,000 available for marketing investments (see also Table 5).

INSERT TABLE 5 ABOUT HERE PLEASE

The model results on the optimal allocation of investment efforts presented in Table 5 reveal the following. In the situation in which we have an boundless investment budget to obtain the overall marketing investment profitability maximum (i.e., an investment budget of \$42,000), the maximum investment profitability level of \$8,894 is obtained if 16.94% of the budget (or \$7.114) is allocated to improving customer perceptions regarding the driver y_4 “delivery” and 83.06% of the budget (or \$34.886) is allocated to improving customer perceptions regarding driver y_5 “product related quality”. Turning to the situation in which a limited investment budget of \$10,000 is assumed, our model indicates that the maximum possible level of marketing investment profitability of \$4,480 is obtained when the entire budget is directed at improving the driver y_5 “product related quality”. These allocation schemes are optimal in the sense that all investment effort allocation schemes different from the derived optimal allocation scheme yield investment profitability levels lower than the projected maximum levels of \$8,894 (effort level of \$42,000) and \$4,480 (effort level of \$10,000) respectively.

Finally, to translate the various optimally allocated investment amounts aimed at improving the different drivers, the input data used to calibrate the relationship between customer driver perceptions and investment costs (see also ADBUDG function in Equation (2)) should be used for interpolation. For example, the \$7,114 suggested to improve driver y_4

“delivery” could correspond with closing contracts with a logistics services company to ensure emergency on-time delivery when needed.

4.6 Investment risk: assessing the robustness of the solution

All (marketing) investments entail uncertainty as the actual financial returns may differ from what was predicted or expected. Consequently, thorough decision making regarding (marketing) investments requires evaluating the projected returns in light of this uncertainty or risk. As risk is reflected by the variability of financial returns (Brealey & Myers, 2000), examining the robustness of the projected profitability as a function of changes in the optimization framework’s parameters provides an excellent way to assess the level of risk associated with the marketing investment decision at hand. Comparable to the notion of risk as variability in returns, the robustness of the solution refers to the variation in the projected optimal financial returns and the financial returns that can be expected under a different set of parameters in the optimization framework. One particular operations research techniques that is valuable in assessing the variability or robustness of the financial returns predicted by our optimization framework is nominal range sensitivity analysis (Morgan & Henrion, 1990; von Winterfeldt & Edwards, 1986). Below we introduce this technique and demonstrate how it can be applied to assess the robustness or risk of the projected investment schemes.

Nominal range sensitivity analysis evaluates the effects on a model’s output due to changes exerted by varying individual model parameters across a range of plausible values while keeping the other parameter values at the nominal or base-case values. The robustness of the model is subsequently expressed as the positive or negative percentage change compared to the nominal solution (Frey & Patil, 2002). For the situation at hand, nominal range sensitivity

analysis is used to assess how the projected optimal solution differs as a function of changes in the parameters of the model explaining the relationship dynamics⁴.

Regarding the set of structural relationships connecting the input variables y_i to loy_c , the impact of a change in one of the structural model's relationships can be determined as follows. If the weight of a certain relation (k, l) is changed, say from w_{kl} to $w'_{kl} = w_{kl} + \delta$, and all other relations remain unchanged, i.e., $w'_{ij} = w_{ij}$ ($(i, j) \neq (k, l)$) parameter $\lambda_{p,q}$ describing the influence of driver z_p on outcome variable z_q as expressed by Equation (7) changes to $\lambda'_{p,q}$ as expressed by Equation (9). Please see Appendix 1 for the complete derivation of Equation (9).

$$\lambda'_{p,q} = \lambda_{p,q} + \lambda_{p,k} \lambda_{l,q} \delta \tag{9}$$

Using Equation (9) we determine the projected investment profitability for various level of δ and compare these figures to the initial optimal investment profitability. In calculating the projected profitability level as a function of δ , we use the investment level and investment allocation scheme that were considered optimal when initially solving the optimization model. Table 6 below summarizes the results for the nominal range sensitivity analysis for the situation at hand.

 INSERT TABLE 6 ABOUT HERE PLEASE

Based on the outcomes of the sensitivity analysis, business market managers can see how much the projected marketing investment profitability deviates from the original optimal profitability level as a function of changes in the decision-making model's parameters. Together

⁴ For assessing the robustness of the solution due to changes in the cost function or the dynamic regression equation used to model the customer monetary value a similar procedure can be followed.

with the expected return on investment of the original optimal solution, the outcomes of the sensitivity analysis provide the required information to make a risk-return trade-off for particular marketing investment initiatives.

5. DISCUSSION AND IMPLICATIONS

Building on relationship marketing theory and operations research techniques, the aim of this study was to develop a decision-making approach that enables business market managers to effectively manage customer relationships in both a customer-oriented and economically justified manner. Regarding the intended contribution of our work the following elements can be discerned. First, we developed and demonstrated a general applicable decision-making or optimization framework to assess critical management issues related to evaluating and optimizing marketing investments. Second, we introduced the concept of sensitivity analysis to assess and understand marketing investment risk.

In line with these two contributions, it needs to be emphasized that although the optimization of marketing efforts to strengthen customer-firm relationship is an often-stated management goal, little work exists on how this can be actually achieved in both a customer-oriented and economically sound manner. This is especially relevant as maximizing financial performance involves optimizing customer perceptions rather than maximizing them. Therefore, the development of our decision-making approach is a logical evolutionary next step in the area of return on marketing initiated by the seminal work of Rust et al. (1995).

In terms of managerial implications we believe our decision-making framework positively impacts business marketing practice in the following ways. First, our optimization framework provides a clear-cut answer to the key issues of how much to invest and how to

allocate these resources in order to maximize marketing investment profitability. Moreover, as a consequence of explicitly balancing the cost and benefits of marketing investments the accompanying rate of return on investment can be readily computed. Besides the informative value of the return on investment figure in isolation, the rate of return stemming from our optimization framework can be compared with alternative and competing investment opportunities such as the purchase of a new piece of equipment. Second, we show how sensitivity analysis of the optimal solution provides a proxy for risk. Consequently, our approach enables decision makers to form a well-informed risk-return trade-off when evaluating different and possibly competing investment opportunities to get the most of their scarce resources. Third, in terms of implementing our decision-making framework in practice it should be stressed that the input needed to calibrate the various elements of the framework are in close reach of the company. Data on customer perceptions needed to model the investment revenues are often already collected by companies on a regular basis, whereas data on customer monetary value is typically readily available in the companies' internal records. Furthermore, the calibration of the ADBUDG function to link investment efforts to marketing investment drivers follows well established lines and requires a relatively limited amount of qualitative research. Fourth, our decision making approach can be used to evaluate and compare different (marketing) investments. Although the main focus of the current paper was on optimizing investment effort and allocation to maximize profitability without imposing a budget constraint the application of the framework is not limited to this. The optimization analysis can be conducted regardless of the available level of investment effort (i.e., investment budget) by imposing a budget constraint. Furthermore, besides searching for an optimal solution the framework can also be used to evaluate and compare the financial consequences of different (marketing) investment initiatives.

Fifth, even though the (financial) data used to calibrate the optimization framework is specific for each company, the structure of the model and its various elements are generally applicable. As will be shown in section six, the general structure of our decision making approach can be easily adapted to different situations than demonstrated here.

6. LIMITATIONS AND EXTENTIONS OF THE OPTIMIZATION FRAMEWORK

Part of the strength of a research project lies in the recognition of its limitations. Although the principal purpose of our empirical study (see also section three) is to serve as a means to demonstrate our decision-making approach, it is relevant to acknowledge that the current sample is not strong enough to draw conclusions on the customer-firm relationship dynamics in business markets in general. More specifically, the fact that data were used from a single company together with the relatively small sample size and its narrow focus seriously limit the generalizability of our empirical findings regarding customer relationship management theory in business settings. Other limitations also include the restricted focus on customer retention for a single company/brand, the exclusion of possible customer differences regarding the various elements of our optimization framework, and the unavailability of data to model longitudinal effects. Furthermore, we did not account for the possible impact of switching costs in explaining customer loyalty intentions. Although probably of minor concern in the current setting, switching costs may be an important determinant of loyalty intentions as evidenced by the work of Han and Sung (2008).

Despite these limitations it might be interesting to show how our optimization model can be extended to incorporate these issues. First, building on the work of Blattberg, Getz, and Thomas (2001) the revenue function in our framework can be extended to include the effects of new

customer acquisition. Furthermore, similar to the work of Rust et al. (2004) brand switching effects can be incorporated in our optimization framework by using a switching matrix rather than the customer's retention probability. Likewise, the model used to explain customer loyalty may be extended to include elements such as perceived switching costs. Second, customer heterogeneity may be explicitly modeled by using specific analysis techniques such as random effects models or MCMC models to estimate the revenue part and subsequently integrate these equations in the optimization model. Third and final, marketing investment efforts may differ in their degree of persistence in influencing marketing investment drivers. On one hand we have investments, such as a computer for better information processing that once it is done, its effect on customer evaluative judgments persists during the succeeding periods. On the other hand, we have marketing initiatives such as investments in staff for which the effects on customer evaluative judgments are reduced once the staff is replaced. To account for these temporal effects the ADBUDG function can be extended with a persistence factor κ , which is high for investments that have a long lasting effect, and low for investments that have a short-term effect only, whereas time series or panel data techniques can be employed to capture dynamic effects in shaping customer evaluative judgments.

7. CONCLUSION

The aim of relationship marketing is to build customer-firm relationships that benefit both parties. In order to achieve this, there is a great need for management tools that quantify both the positive and negative consequences of marketing investments directed at building mutually beneficial customer-firm relationships. The decision-making framework put forward in this paper offers business market managers with a tool to manage marketing investments in both an

economically justified and customer oriented manner. As one of the few existing studies that combines operations research techniques with relationship marketing knowledge in designing a marketing investment decision-making approach, we believe that our work contributes to both business marketing practice and research. In particular our paper extensively shows how our decision-making approach can be used to assess key marketing investment decision issues such as the amount of effort needed to optimize profitability, the calculation of the rate of return on investment, and the design of an optimal investment resource allocation scheme.

APPENDIX 1

Appendix 1 contains additional computational details concerning the application of our decision-making model.

1. MODELING THE MARKETING INVESTMENT REVENUES FUNCTION

The two main elements in our marketing revenues function are customer c 's probability to remain loyal over a time period and his monetary value over that period. Below we outline how we estimated both elements of the revenue function.

1.1 Probability to remain loyal

To include a set of non-recursive structural relationships describing a particular behavioral process in a mathematical decision-making or optimization model the following procedure needs to be followed. First, estimate a structural model describing the relevant relationships among key constructs using SEM or regression-based techniques. Second, use network analysis to determine the total influence of some input variable or driver z_p on a particular outcome variable z_q . Here, the following principles apply. For a non-recursive (acyclic) model in which the variables are indexed in a way that all relations are of the type (z_i, z_j) ($i < j$), i.e., only lower indexed variables influence higher indexed variables (Ahuja, Magnanti, and Orlin, 1993), the influence of any variable on any other variable can be expressed as presented below in Equation (A1.1). If we denote the change in each variable z_i ($i < j$) by Δz_i , then

$$\Delta z_j = \sum_{i < j, (i,j) \in A} w_{ij} \Delta z_i \quad (\text{A1.1})$$

For computing the total influence of driver z_p on outcome variable z_q consider all paths connecting z_p to z_q , and determine the sum of the lengths of these paths. The length of each path is given by the product of the weights of the separate arcs of the path. In mathematical terms, the calculation of the total influence of z_p on z_q , denoted by $\lambda_{p,q}$, is expressed below in Equation (A1.2).

$$\lambda_{p,q} = \sum_{P:(z_p \rightarrow z_q)} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) \quad (\text{A1.2})$$

In Equations (A1.1)-(A1.2) w_{ij} are the different marginal effects of the relevant independent variables on the relevant dependent variables in the set of structural relationships. Please note that the computation of the relevant marginal effects depends on the functional form of the equation. For the situation at hand, the

parameter λ_{pq} needs to be determined for each individual respondent as a consequence of the non-constant marginal effects for logit functions.

1.2 Customer monetary value

Data on customer monetary value typically have a panel design, implying that data is collected across individuals over time. To estimate these models that data set needs to be constructed as having NT rows where N denotes the number of respondents and T are the various time periods over which we collected information about the respondents. To model the data at hand we opted for a dynamic panel data model. Dynamic panel data models are characterized by the presence of a lagged dependent variable among the regressors and are generally expressed as:

$$y_{ct} = \delta y_{c,t-1} + x'_{ct} \beta + u_{ct} \quad c = 1, \dots, N; t = 1, \dots, T; \quad (\text{A1.3})$$

Where y_{ct} denotes the score on variable y of respondent c at time t , x_{ct} are the scores of the c -th respondent on K regressors at time t , δ and β are regression coefficients, and u_{ct} is the model's error component. In modeling panel data the following aspects need to be considered carefully. First of all, due to the inclusion of a lagged-dependent variable as independent variable the assumption of exogeneity no longer may hold. To alleviate the effects of endogeneity Baltagi (2008, p.148) advises to replace the dependent variable y_{ct} by its first difference specification $\Delta y_{ct} = y_{ct} - y_{c,t-1}$ and to use $y_{c,t-2}$ as an instrument for the lagged dependent variable regressor. Second, in contrast to regular cross-sectional regression models, the disturbance term u_{ct} in panel data regression models may consist of following elements: a time-invariant unobservable individual specific effect μ_c , an individual-invariant time effect λ_t , and random remainder error v_{ct} . Depending on whether λ_t is equal to zero or not, a one-way error component model ($u_{ct} = \mu_c + v_{ct}$) or a two-way error component model ($u_{ct} = \mu_c + \lambda_t + v_{ct}$) applies respectively. A Breusch-Pagan Lagrange multiplier test formally assesses whether the hypothesis of λ_t being equal to zero is rejected or not. Finally, the parameter reflecting the time-invariant individual specific effect, μ_c , can be either modeled as a fixed or random effect. A Hausman specification test can be performed to assess whether a fixed or random effects model specification is preferred.

2 MODELING THE MARKETING INVESTMENT COST FUNCTION

The relationship between investment effort and the level of the drivers is modeled using the ADBUDG model suggested by Little (1970). This model offers a simple and flexible tool to calibrate a

variety of S-shaped or concave response functions. The general form of the ADBUDG-function describing the relationship between effort (eff_i) and response y_i is defined as follows:

$$y_i = a_i + (b_i - a_i) \frac{eff_i^{c_i}}{d_i + eff_i^{c_i}} \quad (A1.4)$$

Where:

- y_i = Perceptual variable at which effort is directed / driver
- eff_i = Investment effort in \$
- a_i = Minimum value of y_i when $eff_i = 0$
- b_i = Upper asymptote of scale assessing y_i (corresponds with $eff_i \rightarrow \infty$)
- c_i = Parameter determining shape of response function. Function is concave when $0 < c_i < 1$ and S-shaped when $c_i > 1$
- d_i = Parameter determining shape of response function

Given that the model has only four parameters, only four data points are necessary to calibrate the function in Equation (A1.4). Those four parameters are determined based on interviews with the decision-makers and/or the people at whom the efforts are directed (e.g., customers). Typically, these interviews focus on the following four questions:

- 1) Regarding i what is the current level of effort (eff_i) and to what evaluation does that lead (y_i)? The pair of point corresponds to $(eff(0)_i, y(0)_i)$ on the ADBUDG response curve.
- 2) If effort eff_i is reduced to 0 what will then be the evaluation regarding y_i ? This provides the value for parameter a_i . Usually, a_i reflects the lowest value of the scale on which the perceptions are measured.
- 3) If effort eff_i approaches infinity when will then be the value of y_i ? This answer provides the value for parameter b_i . Usually, b_i reflects the highest value of the scale on which the perceptions are measured.
- 4) If compared to the current situation effort $eff(0)_i$ is doubled to what level of y_i would that lead?

3 THE DERIVATIVE OF THE PROFIT FUNCTION

The derivative of the profit function plays a pivotal role in optimizing marketing investment profitability in terms of optimal investment effort level and the optimal allocation of investment effort. Without engaging in the complex and tedious process of specifying the exact specification of the derivative of the profit function, the following paragraph provides sufficient information to obtain an

intuitive feel for the role the derivative of the profit function plays in the optimization analysis. Please note that we disregard below the investments needed to main the status quo for the sake of simplicity.

The marketing investment profit function is a composite function of the marketing investment revenue function and the marketing investment cost function. As can be clearly seen in Exhibit 1, the dependent variable loy_c in the marketing investment revenues equation is a function of the different drivers y_i , which in turn are a function of marketing investment effort eff_i as implied by the ADBUDG-model. Thus, loy_c is both a function of intermediate variables y_i and independent variable eff_i . According to the chain rule, the derivative of the marketing investment profit function with respect to eff_i is in the format of $\frac{\partial profit}{\partial eff_i} = \frac{\partial profit}{\partial y_i} \cdot \frac{\partial y_i}{\partial eff_i} - 1$. That is, the derivative of the profit function with respect to eff_i is a function of the derivative of the profit function with respect to y_i and the derivative of y_i with respect to eff_i . The term -1 arises from the fact that the total invest effort function is a constant term.

The derivative of the profit function with respect to y_i depends on the magnitude and functional form of the relationships connecting loy_c and y_i (proof of the diffentiability of the revenue function can be obtained from the authors upon request). The derivative of y_i with respect to eff_i equals

$(c_i d_i b_i eff_i^{c_i-1} - c_i d_i a_i eff_i^{c_i-1})(d_i + eff_i^{c_i})^{-2}$ implying that this derivative depends on all ADBUDG-parameters.

As long as $\frac{\partial profit}{\partial eff_i} \geq 0$ investments remain feasible as the incremental investment revenues outweigh the incremental investment efforts.

4 SENSITIVITY ANALYSIS

Mathematically, the notion of nominal range sensitivity analysis is as follows. If the weight of a certain relation (k, l) is changed, say from w_{kl} to $w'_{kl} = w_{kl} + \delta$, and all other relations remain unchanged, i.e., $w'_{ij} = w_{ij}$ ($(i, j) \neq (k, l)$) parameter $\lambda_{p,q}$ describing the influence of driver z_p on outcome variable z_q as expressed by Equation (A1.2) changes to $\lambda'_{p,q}$ as follows.

$$\begin{aligned}
\lambda'_{p,q} &= \sum_{P:(z_p \rightarrow z_q)} \left(\prod_{(z_i, z_j) \in P} w'_{ij} \right) \\
&= \sum_{P:(z_p \rightarrow z_q)(k,l) \notin P} \left(\prod_{(z_i, z_j) \in P} w'_{ij} \right) + \sum_{P:(z_p \rightarrow z_q)(k,l) \in P} \left(\prod_{(z_i, z_j) \in P} w'_{ij} \right) \\
&= \sum_{P:(z_p \rightarrow z_q)(k,l) \notin P} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) + \sum_{P:(z_p \rightarrow z_q)(k,l) \in P} \left(\prod_{(z_i, z_j) \in P-(k,l)} w_{ij} \right) (w_{kl} + \delta) \\
&= \sum_{P:(z_p \rightarrow z_q)(k,l) \notin P} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) + \sum_{P:(z_p \rightarrow z_q)(k,l) \in P} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) + \sum_{P:(z_p \rightarrow z_q)(k,l) \in P} \left(\prod_{(z_i, z_j) \in P-(k,l)} w_{ij} \right) \delta
\end{aligned} \tag{A1.5}$$

The first two terms in the last row of Equation (A1.5) add up to $\lambda_{p,q}$, whereas the last term (excluding parameter δ) in the last row of Equation (A1.5) can be written as:

$$\sum_{P:(z_p \rightarrow z_q)(k,l) \in P} \left(\prod_{(z_i, z_j) \in P-(k,l)} w_{ij} \right) = \sum_{P:(z_p \rightarrow z_q)} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) \cdot \sum_{P:(z_p \rightarrow z_q)} \left(\prod_{(z_i, z_j) \in P} w_{ij} \right) = \gamma_{p,k} \cdot \gamma_{l,q} \tag{A1.6}$$

Thus, substituting Equation (A1.6) for the corresponding term in Equation (A1.5) yields the following expression (see Equation (A1.7)) to calculate the influence of driver z_p on outcome variable z_q as a function of changes in the structural model parameters.

$$\lambda'_{p,q} = \lambda_{p,q} + \lambda_{p,k} \lambda_{l,q} \delta \tag{A1.7}$$

Using the optimal investment effort allocation scheme, compute the marketing investment profitability obtained with $\lambda'_{p,q}$. Now, the robustness of the optimal solution is obtained by computing the relative difference in investment profitability obtained for parameters $\lambda_{p,q}$ (original coefficients) and $\lambda'_{p,q}$ (altered coefficients). The robustness of the optimal solution is defined as

$$\left[\frac{\left| \text{profit}(\lambda_{p,q}) - \text{profit}(\lambda'_{p,q}) \right|}{\text{profit}(\lambda_{p,q})} \right] * 100\%. \text{ Note that in assessing the robustness of the optimal solution,}$$

total profit is used rather than investment profit.

Regarding the situation described in the paper, for which we have nonlinear structural relationships underlying the revenue generating process and thus the marketing investment profitability calculation, the effect of changes in the model parameters (the δ parameter in the sensitivity analysis) on the outcome variable is not constant per respondent. Consequently, the function to determine the marketing investment profitability under $\lambda'_{p,q}$ contains a separate $\lambda'_{p,q}$ parameter for each respondent.

5 OPTIMIZATION SOFTWARE

Our decision-making model was programmed in AIMMS. This software package was subsequently used to run all optimization analyses in this paper. AIMMS is an advanced development environment for building optimization based operation research applications and is used by leading companies throughout the world to support many different aspects of decision making.

For the purpose of this paper all programming was done in the mathematical programming language that is originally used in AIMMS. However, very recently AIMMS developed an add-in for Microsoft Excel allowing to run optimization analyses like the ones described in this paper in an Excel setting. This development makes the practical application of our marketing investment decision-making tool more accessible and attractive for prospective users.

APPENDIX 2: PRACTICAL IMPLEMENTATION OF THE DECISION-MAKING APPROACH

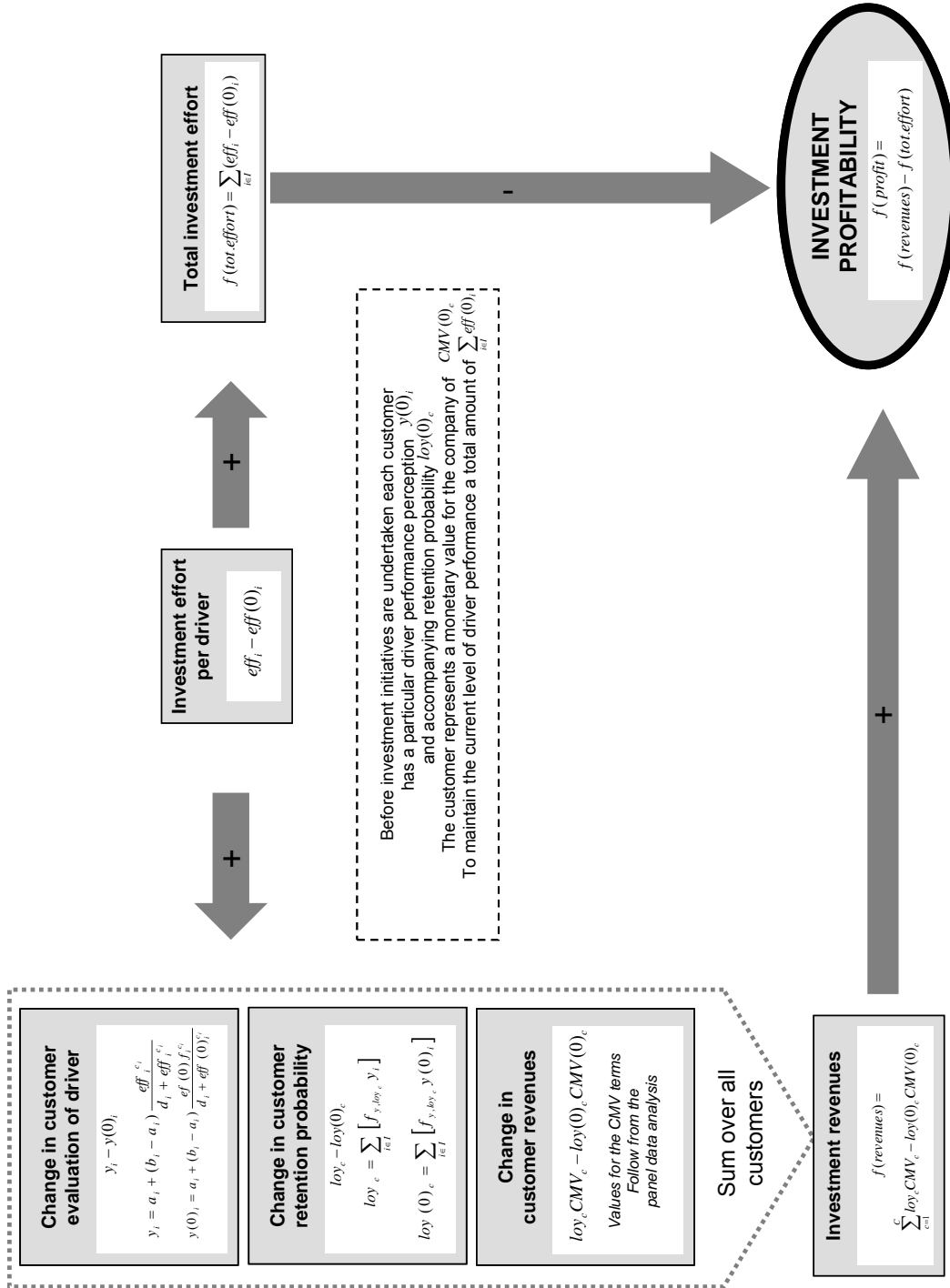
The aim of Appendix 2 is to provide guidance for the practical implementation of the proposed decision-making approach. More specifically, without restricting ourselves to a specific programming language Appendix 2 explains in very simple terms (i.e. minimum of mathematical notation) the steps that are involved in using the decision-making approach. The explanation below describes the practical implementation on two different levels. First, the implementation in general terms. Second, a simple example model is used to further clarify the practical implementation in the gray areas.

1. OVERVIEW OF THE OPTIMIZATION PROCESS

Before turning to the outline of the various steps involved in implementing the decision-making approach, it may be useful to provide a schematic overview of the process underlying the optimization routine. Figure A2.1 below provides a graphical overview of the optimization process that forms the core of our decision-making approach.

The optimization process presented in Figure A2.1 states that investment profitability is the difference between investment revenues and total investment efforts. Both the level of total investment effort and investment revenues vary as a function of the amount of investment effort directed at improving customer perceptions of the various drivers. On the revenue side of Figure A2.1 investment effort at the driver level leads to an increase in customer perceptions of this driver and ignites a chain of effects resulting in enhanced customer revenues via an increase in the customer's retention probability. On the right hand side of Figure A2.1, the different amounts of the investment effort summed over the various drivers yield an estimate of the total investment effort. Determining the optimal solution (i.e. maximum level of investment profitability) involves an iterative procedure until some convergence criterion is met.

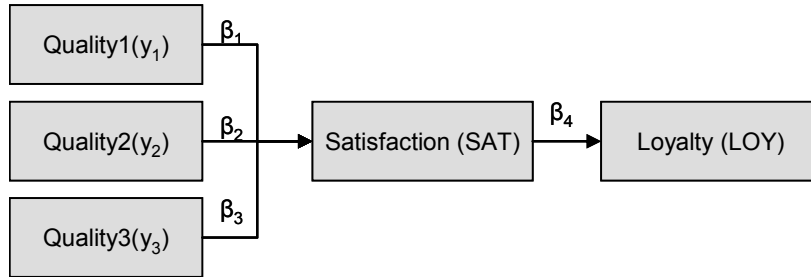
Figure A2.1: Graphical overview optimization process



2. EXAMPLE MODEL

The linear model presented below in Figure A2.2 describing the relationship among a set of three drivers and customer loyalty is used to demonstrate the practical application of our decision-making framework. Furthermore, we assume that there are only three customers ($c = 1,2,3$).

Figure A2.2: Example model



Similar to the situation described in the paper, the following assumptions underlie our decision-making approach.

- Under the current situation (i.e. status quo level or no investments) the perceived performance on the drivers is $y(0)_1$, $y(0)_2$, $y(0)_3$ and the accompanying customer loyalty is $loy(0)_k$
- Under the status quo level, the perceived driver performance $y(0)_1$, $y(0)_2$, $y(0)_3$ is the result of spending $eff(0)_1$, $eff(0)_2$, and $eff(0)_3$ respectively.
- The ADBUDG function is used to describe the relationship between the level of the drivers y_1 , y_2 , y_3 and investment effort (eff_i)
- Each customer spends an amount of CMV_c in the subsequent time period and an amount of $CMV(0)_c$ in the current period.
- At the customer level, customer revenues are calculated as the product of the customers' retention probability and the amount they spend.

3. IMPLEMENTATION OF THE OPTIMIZATION PROCESS

The core of our decision-making approach is formed by the optimization process outlined in Figure A2.1. As with every optimization problem, the aim is to optimize some objective function. In our framework this is the maximization of the investment profit function. In more formal notation, this can be summarized as shown in Equation (A2.1a).

$$\text{Maximize } f(\textit{profit}) \tag{A2.1a}$$

As the profit function $f(\textit{profit})$ equals the difference between the revenues function $f(\textit{revenues})$ and total investment effort function $f(\textit{tot.effort})$, an alternative way of expressing the optimization of the objective function is shown in Equation (A2.1b).

$$\text{Maximize } f(\textit{revenues}) - f(\textit{tot.effort}) \tag{A2.1b}$$

The procedures needed to define the revenues function $f(\textit{revenues})$ and investment effort $f(\textit{tot.effort})$ function will be outlined in the paragraphs 3.1 and 3.2 respectively.

3.1 THE REVENUES FUNCTION $f(\textit{revenues})$

The investment revenues per customer are a function of the change in the customer's retention probability loy_c and the customer's contribution margin CMV_c . Furthermore, as each customer already has a relationship with the firm, we need to model the investment revenues relative to the customer loyalty probability ($loy(0)_c$) and the amount of customer monetary value ($CMV(0)_c$) before the investment initiative is undertaken. Thus, at the level of the individual customer the revenue function is defined as shown in Equation (A2.2a).

$$f(\textit{revenues}) = \textit{loy}_c \textit{CMV}_c - \textit{loy}(0)_c \textit{CMV}(0)_c \tag{A2.2a}$$

The total investment revenues are determined by summing the revenue function over all c customers.

Thus, in a situation of only three customers as in the example guiding this Appendix the revenue

function becomes

$$f(\text{revenues}) = (\text{loy}_1 \text{CMV}_1 - \text{loy}(0)_1 \text{CMV}(0)_1) + (\text{loy}_2 \text{CMV}_2 - \text{loy}(0)_2 \text{CMV}_2) \\ + (\text{loy}_3 \text{CMV}_3 - \text{loy}(0)_3 \text{CMV}_3)$$

The terms loy_c and CMV_c in the revenue function $f(\text{revenue})$ are determined as follows.

3.1.1 Customer monetary value and the revenues function $f(\text{revenue})$

The figures for the terms $\text{CMV}(0)_c$ and CMV_c are derived from the internal company data base containing information on customer contribution margins. For the study at hand, a dynamic regression model was estimated (see also Equation (A1.3)). The term $\text{CMV}(0)_c$ represents the contribution margin of customer c in the three months before the study and is derived directly from the company data base. The term CMV_c represents the expected contribution margin of customer c over the first quarter after the data collection and is predicted using a panel regression model.

3.1.2 Customer retention probability and the revenues function $f(\text{revenue})$

Investments aimed at improving customer's driver perceptions form the starting point to increasing the customer's retention probability and thus financial performance. The magnitude of the relationship between the customer's retention probability and the different drivers is captured by the term

$f_{y_i, \text{loy}}$ in the expression $\text{loy} = \sum_{i \in I} f_{y_i, \text{loy}} y_i$ (see also Equation (5a) in paper). More specifically,

$f_{y_i, \text{loy}}$ describes the amount of change in the customer retention probability caused by changes in variable y_i . The term $f_{y_i, \text{loy}}$ equals the product of the marginal effects for each path connecting y_i and loy and subsequently summing these products over all relevant paths connecting y_i and loy . See also Appendix 1 Equations (A1.1)-(A1.2) for the exact calculation.

The values for $y(0)_i$ stems from the survey data and are customer c 's evaluations of the relevant input variables. Note that the values for $y(0)_i$ typically vary across customers.

The (optimal) value for y_i needed to calculate the customer retention probability and revenues is determined during the optimization analysis as a function of the level of investment effort eff_i . The exact nature of the relationship between y_i and eff_i is captured by the ADBUDG function.

For the example model which contains only linear relationships the term $f_{y,loy}$ boils down to

$\sum_{i \in I} \lambda_i y_i$ where λ_i is the relation between the i -th driver and the customer retention

probability loy_c . Applying Equations (1.1) and (1.2) to the coefficients in Figure (A2.2) leads

to: $\lambda_1 = \beta_1 \beta_4$, $\lambda_2 = \beta_2 \beta_4$, and $\lambda_3 = \beta_3 \beta_4$.

As such, the terms loy and $loy(0)$ in revenues function $f(revenues)$ can be written respectively as $loy = \lambda_1 y_1 + \lambda_2 y_2 + \lambda_3 y_3$ and $loy(0) = \lambda_1 y(0)_1 + \lambda_2 y(0)_2 + \lambda_3 y(0)_3$ where the term $loy(0)$ differs per customer depending the customer's driver perceptions $y(0)_1, y(0)_2, y(0)_3$.

3.2 The investment effort function $f(tot.effort)$

The ADBUDG function is the foundation for the investment effort function $f(tot.effort)$. For each driver y_i the ABDUDG function needs to be calibrated to describe the link between the customer's perceptions of the relevant driver (y_i) and the amount of investment effort (eff_i) needed to improve the particular driver. The various ADBUDG parameters are calibrated using the procedure outlined in Appendix 1. The amount of total investment reflected by function $f(tot.effort)$ equals the sum of different amounts of investment eff_i directed to the various drivers y_i .

In terms of the example model this implies that three effort functions are specified. That is, for each driver a separate ADBUDG function is needed.

$$y_1 = a_1 + (b_1 - a_1) \frac{eff_1^{c_1}}{d_1 + eff_1^{c_1}}$$

$$y_2 = a_2 + (b_2 - a_2) \frac{eff_2^{c_2}}{d_2 + eff_2^{c_2}}$$

$$y_3 = a_3 + (b_3 - a_3) \frac{eff_3^{c_3}}{d_3 + eff_3^{c_3}}$$

Furthermore, the function for the total level of investment effort is

$$f(tot.effort) = eff_1 + eff_2 + eff_3$$

3.3 The constraints

Specification of the constraints ensures that the relationships of the optimization analysis follow the predetermined structure. More particularly, we impose the following constraints.

3.3.1 Constraint 1

Constraint that describes the nature of the relationship between the drivers and the customer retention probability. This constraint reflects the theoretical framework underlying the nomological web of relations among the input variables y_i and the retention probability loy_c . For the situation at hand, this

constraint is summarized as $loy_c = \sum_{i \in I} [f_{y_i, loy_c} y_i]$.

3.3.2 Constraint 2

Constraint that describes the nature of the relationship between the level of the input variables and the amount of investment effort directed at them. This constraint equals the ADBUDG function for the different drivers.

3.3.3 Constraint 3

Budget constraint that states that the available amount of total investment effort is capped by a pre-determined maximum or budget B . Note that this constraint may be relaxed by setting the budget B equal to infinity. This constraint is formally denoted as $f(tot.effort) \leq B$ or equivalently $\sum_{i \in I} eff_i \leq B$

3.3.4 Constraint 4

Constraint that restricts the level of investment effort to a minimum value of zero. That is, minimum of investment effort eff_i directed to a driver y_i is zero. More formally, $eff_i \geq 0$.

Overall, the decision-making framework for the example in this Appendix can be summarized as follows.

Maximize

$$(loy_1 CMV_1 - loy(0)_1 CMV(0)_1) + (loy_2 CMV_2 - loy(0)_2 CMV(0)_2) + (loy_3 CMV_3 - loy(0)_3 CMV(0)_3) - (eff_1 - eff(0)_1) + (eff_2 - eff(0)_2) + (eff_3 - eff(0)_3)$$

Subject to:

Constraint 1

$$loy = \beta_1\beta_4y_1 + \beta_2\beta_4y_2 + \beta_3\beta_4y_3$$

Constraint 2

$$y_1 = a_1 + (b_1 - a_1) \frac{eff_1^{c_1}}{d_1 + eff_1^{c_1}}$$

$$y_2 = a_2 + (b_2 - a_2) \frac{eff_2^{c_2}}{d_2 + eff_2^{c_2}}$$

$$y_3 = a_3 + (b_3 - a_3) \frac{eff_3^{c_3}}{d_3 + eff_3^{c_3}}$$

Constraint 3

$$(eff_1 - eff(0)_1) + (eff_2 - eff(0)_2) + (eff_3 - eff(0)_3) \leq Budget$$

Constraint 4

$$(eff_1 - eff(0)_1) \geq 0$$

$$(eff_2 - eff(0)_2) \geq 0$$

$$(eff_3 - eff(0)_3) \geq 0$$

4. CONDUCTING THE OPTIMIZATION ANALYSIS

This section provides an overview of how the different analysis stemming from our optimization approach can be conducted.

4.1 Optimal level of investment effort

This type of analysis can be performed in two ways. The most appropriate way is by determining the derivative of the profit function with respect to investment effort, setting this derivative equal to zero, and having the program solve this equation. As shown in Appendix 1 this often involves a long and complex derivation. An alternative way to determining the optimal level of investment effort is by running the optimization framework for a series of different budgets and manually look for the optimum level of investment effort. In particular, plotting the profitability levels against the budgets then provides a simple way to find the optimal investment effort level (see also for example Figure 2 in the paper).

4.2 Optimal allocation of investment effort

Running the optimization analysis with the optimal investment effort level as budget constraint provides a solution containing the optimal effort level per driver. The solution contains values for both y_i and eff_i . It may be convenient to express the allocation of investment effort in relative terms. To do this, calculate the fraction $(eff_i - eff(0)_i) / \sum_{i \in I} (eff_i - eff(0)_i)$ for each driver. Finally, use the data to calibrate the ADBUDG function to derive the actual investment action corresponding with the optimal effort levels per driver.

4.3 Return on investment

The investment effort level and the resulting profitability level stemming from the optimization analysis provide sufficient information to calculate the rate of return on investment expressed by Equation (9) in the paper.

4.4 Robustness of the optimal solution

Nominal range sensitivity analysis involves examining how the optimal solution changes as a result of altering a single parameter in the model while keeping the other parameters at their base-case values. Nominal range sensitivity analysis for the model parameters linking the drivers to the customer retention probability (i.e. part of $f(revenues)$) proceeds as follows.

First, use the total profitability level (i.e. including the profitability at the status quo level) of the original optimal solution as a baseline for comparison. Second, determine the consequences of a change in a single model parameter using Equation (A1.7). Third, determine the level of total profitability that would be obtained under the original optimal investment level allocation taking into the changed model parameter. Fourth, determine the relative change in projected investment profitability as described in Appendix 1.

It should be noted that a similar procedure may also be performed on the functions related to the investment effort.

Original optimal solution is based on parameters λ_{14} , λ_{24} , and λ_{34} and spending amounts eff_1 , eff_2 , and eff_3 to the respective drivers. This yields an optimal profit level of

$$profit(\lambda_{14}, \lambda_{24}, \lambda_{34}) = (y_1 \lambda_{14} + y_2 \lambda_{24} + y_3 \lambda_{34}) - (eff_1 + eff_2 + eff_3).$$

As we assume that the cost function remains stable, the driver levels resulting from the optimal

allocation scheme are unaffected by changes in the customer retention model. To assess the robustness of the optimal profitability level as the different parameters would alter by δ we proceed as follows.

Path between Qual1(y_1) and Satisfaction (SAT)

If parameter β_1 increases with δ , resulting into $\beta_1 + \delta$, $\lambda_{14} = \beta_1\beta_4$ changes to

$\lambda'_{14} = (\beta_1 + \delta)\beta_4 = \beta_1\beta_4 + \delta\beta_4$ (see also Equation (A1.7)). This will in turn yield a profit level of $profit(\lambda'_{14}, \lambda_{24}, \lambda_{34}) = (y_1\lambda'_{14} + y_2\lambda_{24} + y_3\lambda_{34}) - (eff_1 + eff_2 + eff_3)$

Path between Qual2(y_2) and Satisfaction (SAT)

If parameter β_2 increases with δ , resulting into $\beta_2 + \delta$, $\lambda_{24} = \beta_2\beta_4$ changes to

$\lambda'_{24} = (\beta_2 + \delta)\beta_4 = \beta_2\beta_4 + \delta\beta_4$ (see also Equation (A1.7)). This will in turn yield a profit level of $profit(\lambda_{14}, \lambda'_{24}, \lambda_{34}) = (y_1\lambda_{14} + y_2\lambda'_{24} + y_3\lambda_{34}) - (eff_1 + eff_2 + eff_3)$

Path between Qual3(y_3) and Satisfaction (SAT)

If parameter β_3 increases with δ , resulting into $\beta_3 + \delta$, $\lambda_{34} = \beta_3\beta_4$ changes to

$\lambda'_{34} = (\beta_3 + \delta)\beta_4 = \beta_3\beta_4 + \delta\beta_4$ (see also Equation (A1.7)). This will in turn yield a profit level of $profit(\lambda_{14}, \lambda_{24}, \lambda'_{34}) = (y_1\lambda_{14} + y_2\lambda_{24} + y_3\lambda'_{34}) - (eff_1 + eff_2 + eff_3)$

Path between Satisfaction (SAT) and Loyalty (LOY)

An increase in parameter β_4 with δ , resulting into $\beta_4 + \delta$, has consequences for the relationships among each of the quality variables y_1 y_2 y_3 and LOY . More specifically, the impact of y_1 on

LOY changes from $\lambda_{14} = \beta_1\beta_4$ into $\lambda'_{14} = \beta_1(\beta_4 + \delta) = \beta_1\beta_4 + \delta\beta_1$; impact of y_2 on LOY changes from $\lambda_{24} = \beta_2\beta_4$ into $\lambda'_{24} = \beta_2(\beta_4 + \delta) = \beta_2\beta_4 + \delta\beta_2$; and the impact of y_3 on LOY changes from $\lambda_{34} = \beta_3\beta_4$ into $\lambda'_{34} = \beta_3(\beta_4 + \delta) = \beta_3\beta_4 + \delta\beta_3$.

With $profit(\lambda'_{14}, \lambda'_{24}, \lambda'_{34}) = (y_1\lambda'_{14} + y_2\lambda'_{24} + y_3\lambda'_{34}) - (eff_1 + eff_2 + eff_3)$ as the accompanying profitability level.

Now, compare the new level of profitability with original optimal level of profitability for each of the changed parameters.

Path between Qual1(y_1) and Satisfaction (SAT)

$$\left(\frac{\text{profit}(\lambda'_{14}, \lambda_{24}, \lambda_{34}) - \text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})}{\text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})} \right) * 100\%$$

Path between Qual2(y_2) and Satisfaction (SAT)

$$\left(\frac{\text{profit}(\lambda_{14}, \lambda'_{24}, \lambda_{34}) - \text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})}{\text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})} \right) * 100\%$$

Path between Qual3(y_3) and Satisfaction (SAT)

$$\left(\frac{\text{profit}(\lambda_{14}, \lambda_{24}, \lambda'_{34}) - \text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})}{\text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})} \right) * 100\%$$

Path between Satisfaction (SAT) and Loyalty (LOY)

$$\left(\frac{\text{profit}(\lambda'_{14}, \lambda'_{24}, \lambda'_{34}) - \text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})}{\text{profit}(\lambda_{14}, \lambda_{24}, \lambda_{34})} \right) * 100\%$$

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Table 1: Literature overview relationship dynamics

Relationship	Literature in support of the hypothesized relationship
QUAL → VALUE	Cronin et al. (2000); Sweeney et al. (1999); Bolton and Drew (1991)
QUAL → SAT	Lewin (2008); Cronin et al. (2000); Bolton (1998); Anderson and Sullivan (1993)
VALUE → SAT	Lewin (2008); Lam et al. (2004); Cronin et al. (2000)
SAT → TRUST	Selnes (1998); Ganesan (1994)
QUAL → TRUST	Singh and Sirdeshmukh (2000); Gounaris (2005)
VALUE → SAT	Lewin (2008); Lam et al. (2004)
VALUE → TRUST	Gwinner et al. (1998)
SAT → LOY	Lewin (2008); Lam et al. (2004); Anderson and Sullivan (1993)
TRUST → LOY	Keh and Xie (2008) Garbarino and Johnson (1999), Singh and Sirdeshmukh (2000)
QUAL → LOY	Nijssen et al. (2003), Cronin et al. (2000)
VALUE → LOY	Lam et al. (2004); Cronin et al. (2000)

Table 2: Descriptive statistics and psychometric properties

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 QUAL1	1																	
2 QUAL2	0.56	1																
3 QUAL3	0.34	0.36	1															
4 QUAL4	0.42	0.37	0.23	1														
5 QUAL5	0.39	0.54	0.35	0.32	1													
6 QUAL6	0.33	0.39	0.32	0.34	0.41	1												
7 QUAL7	0.43	0.37	0.23	0.26	0.39	0.43	1											
8 SAT	0.48	0.55	0.31	0.33	0.57	0.48	0.45	1										
9 VALUE1	0.23	0.23	0.13	0.14	0.14	0.20	0.17	0.30	1									
10 VALUE2	0.30	0.35	0.13	0.24	0.32	0.25	0.25	0.41	0.66	1								
11 VALUE3	0.27	0.26	0.16	0.29	0.24	0.18	0.25	0.36	0.59	0.55	1							
12 VALUE4	0.20	0.26	0.17	0.23	0.35	0.21	0.20	0.37	0.45	0.46	0.45	1						
13 TRUST1	0.22	0.22	0.14	0.18	0.18	0.18	0.22	0.33	0.47	0.47	0.41	0.33	1					
14 TRUST2	0.15	0.23	0.22	0.12	0.15	0.11	0.14	0.36	0.32	0.33	0.36	0.20	0.56	1				
15 TRUST3	0.17	0.29	0.05	0.15	0.23	0.14	0.16	0.35	0.40	0.41	0.39	0.29	0.59	0.57	1			
16 TRUST4	0.16	0.23	0.21	0.24	0.16	0.13	0.09	0.30	0.29	0.33	0.31	0.19	0.60	0.58	0.61	1		
17 TRUST5	0.13	0.31	0.12	0.19	0.21	0.12	0.16	0.37	0.45	0.45	0.45	0.35	0.64	0.57	0.72	0.68	1	
18 P(LOY)	0.20	0.26	0.07	0.27	0.29	0.04	0.18	0.36	0.25	0.32	0.38	0.28	0.32	0.23	0.34	0.24	0.41	1
MEAN	7.82	7.61	6.97	7.50	7.50	7.52	7.49	8.76	8.20	8.47	8.68	6.85	8.58	7.44	8.63	7.75	8.33	0.72
S.D.	0.64	0.71	0.91	0.97	0.70	0.88	0.80	0.68	1.95	2.30	2.07	3.30	2.28	2.48	2.13	2.39	2.22	0.23
LOADING	0.70	0.80	0.44	0.54	0.82	0.67	0.64	n.a.	0.74	0.87	0.83	0.72	0.83	0.77	0.85	0.82	0.89	n.a.
LOWER BOUND	0.56	0.69	0.22	0.32	0.70	0.53	0.48	n.a.	0.57	0.74	0.71	0.54	0.76	0.68	0.78	0.73	0.84	n.a.
UPPER BOUND	0.82	0.90	0.65	0.73	0.91	0.80	0.78	n.a.	0.86	0.86	0.92	0.96	0.88	0.83	0.89	0.87	0.92	n.a.
1 ST EIGENVALUE	n.a.							n.a.	2.59			3.46						n.a.
2 ND EIGENVALUE	n.a.							n.a.	0.62			0.48						n.a.
CRONBACH'S α	n.a.							n.a.	0.78			0.89						n.a.
AVE	n.a.							n.a.	0.63			0.69						n.a.

Table 3: Empirical results structural model

Relationship	Unstandardized coefficient	Standardized coefficient	Bias corrected bootstrap percentile confidence interval	Adjusted R² bootstrap percentile confidence interval
QUAL → VAL	0.595	0.446	[0.259;0.534]	VAL: R ² (adj)=0.199*
QUAL → SAT	0.763	0.606	[0.476;0.702]	SAT: [0.489;0.508]
VAL → SAT	0.181	0.192	[0.069;0.327]	
QUAL → TRUST	<i>Not significant</i>	<i>Not significant</i>	<i>Not significant</i>	TRUST: [0.309;0.325]
VAL → TRUST	0.436	0.448	[0.281;0.569]	
SAT → TRUST	0.208	0.202	[0.089;0.326]	
QUAL → P(LOY)	<i>Not significant</i>	<i>Not significant</i>	<i>Not significant</i>	P(LOY): [0.288;0.323]
VAL → P(LOY)	0.993	0.277	[0.097;0.435]	
SAT → P(LOY)	0.558	0.147	[0.006;0.300]	
TRUST → P(LOY)	0.999	0.271	[0.098;0.326]	

* As VAL is a function of just an endogenous construct it is not possible to construct a bootstrap percentile confidence interval for its R² (adj) value.

Table 4: Empirical results dynamic regression analysis

Independent variables	Explanation dummy variables	Unstandardized coefficient	t-value (p-value)
$CMV_{c,t-1}$		0.30	6.60 (p<0.0001)
$QUANT_{c,t-2}$		0.64	23.06 (p<0.0001)
$SIZE1_c$	Compares size quartiles 1 and 2	1652	3.00 (p=0028)
$SIZE2_c$	Compares size quartile 1 and 3	6929	9.13 (p<0.0001)
$TYPE1_c$	Compares user of product line B to those of product line A	n.s.	
$TYPE2_c$	Compares used of product lines A and B to those of product line A	n.s.	
REL_c		n.s.	

Table 5: Optimal investment strategies

Short description of driver	Qual1 (y₁) Ordering (e.g. accessibility)	Qual2 (y₂) Information requests (e.g. knowledge employees)	Qual3 (y₃) Catalogue (e.g. accessibility)	Qual4 (y₄) Delivery (e.g. timeliness)	Qual5 (y₅) Product related quality (e.g. assortment)	Qual6 (y₆) Complaint management (e.g. first time fix)	Qual7 (y₇) Invoicing (e.g. clarity)
Pre-investment level of driver	7.82	7.61	6.97	6.5	6.5	7.52	7.49
Effort to main current level	\$179,358	\$159,205	\$115,017	\$92,857	\$92,857	\$151,613	\$149,203
Average impact of driver on retention probability for customer <i>c</i>	0.0164	0.0191	0.0103	0.0133	0.0187	0.0135	0.0149
Optimal total effort level \$42,000							
Optimal allocation over drivers	0%	0%	0%	16.94%	83.06%	0%	0%
Optimal effort level	\$0	\$0	\$0	\$7,114	\$34,886	\$0	\$0
Post-investment level of driver	7.82	7.61	6.97	6.67	7.19	7.52	7.49
Change in level of driver	0	0	0	0.17	0.69	0	0
Budget constraint of \$10,000 total effort level							
Optimal allocation over drivers	0%	0%	0%	0%	100%	0%	0%
Optimal effort level	0	0	0	0	\$10,000	0	0
Post-investment level of driver	7.82	7.61	6.97	6.5	6.73	7.52	7.49
Change in level of driver	0	0	0	0	0.23	0	0

Table 6: Sensitivity analysis

Path	W _{ij} - 5%			W _{ij} + 5%		
	Investment profitability	Δ%	ROI (%)	Investment profitability	Δ%	ROI (%)
Qual1 → Quality	\$ 11,984	35	28.51	\$ 4,136	53	9.85
Qual2 → Quality	\$ 11,794	33	28.08	\$ 6,230	30	14.83
Qual3 → Quality	\$ 10,196	15	24.28	\$ 7,640	14	18.19
Qual4 → Quality	\$ 10,596	19	25.23	\$ 7,286	18	17.35
Qual5 → Quality	\$ 9,614	8	22.89	\$ 8,185	8	19.49
Qual6 → Quality	\$ 10,969	23	26.12	\$ 6,940	22	16.52
Qual7 → Quality	\$ 11,018	24	26.23	\$ 6,900	22	16.43
Quality → Value	\$ 16,982	91	40.43	\$ 2,594	71	6.18
Quality → Satisfaction	\$ 15,617	76	37.18	\$ 3,929	56	9.35
Value → Satisfaction	\$ 14,124	59	33.63	\$ 4,691	47	11.17
Satisfaction → Trust	\$ 10,429	17	24.83	\$ 6,730	24	16.02
Value → Trust	\$ 14,270	61	33.98	\$ 3,938	56	9.38
Value → Loyalty	\$ 13,556	53	32.28	\$ 4,580	48	10.90
Satisfaction → Loyalty	\$ 14,447	63	34.40	\$ 2,945	67	7.01
Trust → Loyalty	\$ 15,900	79	37.86	\$ 3,238	64	7.71

Figure 1: Overview of the key elements of the optimization framework

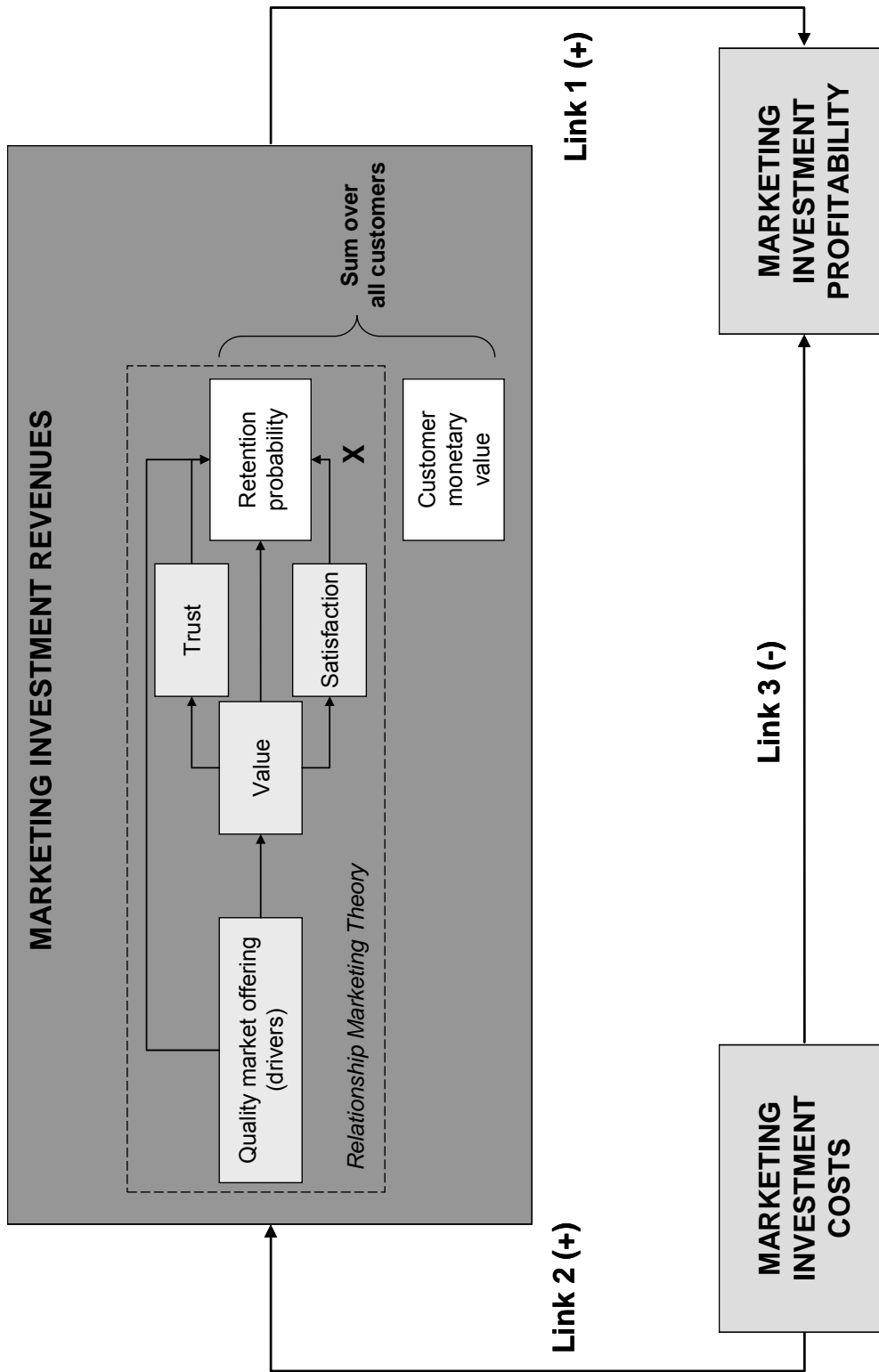


Figure 2: Investment effort, investment revenues, and investment profitability

