Moving beyond intuition—Managing allocation decisions in relationship marketing in business-to-business markets

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Abstract

Developing and estimating structural models is becoming a routine practice in marketing. In this study, the possibilities of applying such models in managerial decision making under uncertainty are investigated. In particular the feasibility of exploiting the inherent probabilistic nature of structural models to buttress decision making is demonstrated. The approach is based on making heavy use of standard simulation routines. The model that is under scrutiny describes the relationships between firms' efforts in three areas (the offer, customer relationships, and market positions) on the success of a new product introduction. Special attention is given to the aspect of risk aversion. Accounting for the risk attitude implies different allocation decisions for risk-averse compared to risk-prone managers, in line with common sense.
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Keywords: Structural equation models; Decision making; Simulation; Risk

1. Introduction

Structural equation modeling (SEM) is becoming standard practice in the marketing society nowadays. The benefits of SEM are well known: SEM is a rigorous and conceptually comprehensive approach that addresses fundamental issues, using fundamental constructs. The results of SEM are an increased understanding of underlying relationships with quantitative assessments of the relative importance of effects. The use of SEM in decision-making situations has been practically absent, however. This paper explores the possibilities for this usage of SEM.

A companion paper (De Ruyter, Moorman, & Lemmink, 2001) described the construction and estimation of a model that explained how customer loyalty depends on the efforts of management in various areas in the case of launching a new product. In that paper, three main areas that serve as antecedents were identified, namely, the offer, relationships, and market position. Intermediary variables are calculative

commitment, affective commitment, and trust. The conceptual model that was developed is depicted in Fig. 1, together with some selected references (E. W. Anderson & Weitz, 1992; J. C. Anderson & Narus, 1990, 1999; Cunningham & Tynan, 1993; Dick & Basu, 1994; Gemunden & Walter, 1994; Geyskens, Steenkamp, Scheer, & Kumar, 1996; Heide & John, 1988; Kumar, Hibbard, & Stern, 1994; MacKenzie, 1992; Moorman, Zaltman, & Deshpandé, 1992; Morgan & Hunt, 1994). The estimated model is reported in Fig. 2. Goodness-of-fit criteria were at least satisfactory; see De Ruyter et al. (2001) for an elaborate discussion of the model.

Basically the model describes how loyalty intentions are influenced by the perceptions of the customer of the company's "offer," the perception of the "relationship" between customer and company and the company's perceived "market position." Obviously, by active marketing, management can influence these customer perceptions and, consequently, management may seek for optimal levels in the three fields. However, the question becomes how this marketing is efficiently done, or alternatively, in marginal terms: How should an additional dollar be spent, given a certain, current position? The structural model can be used to answer such optimization questions.

In this paper the focus will be on how structural equations models can be used for decision-making analysis. As usual, decision making takes place under conditions of

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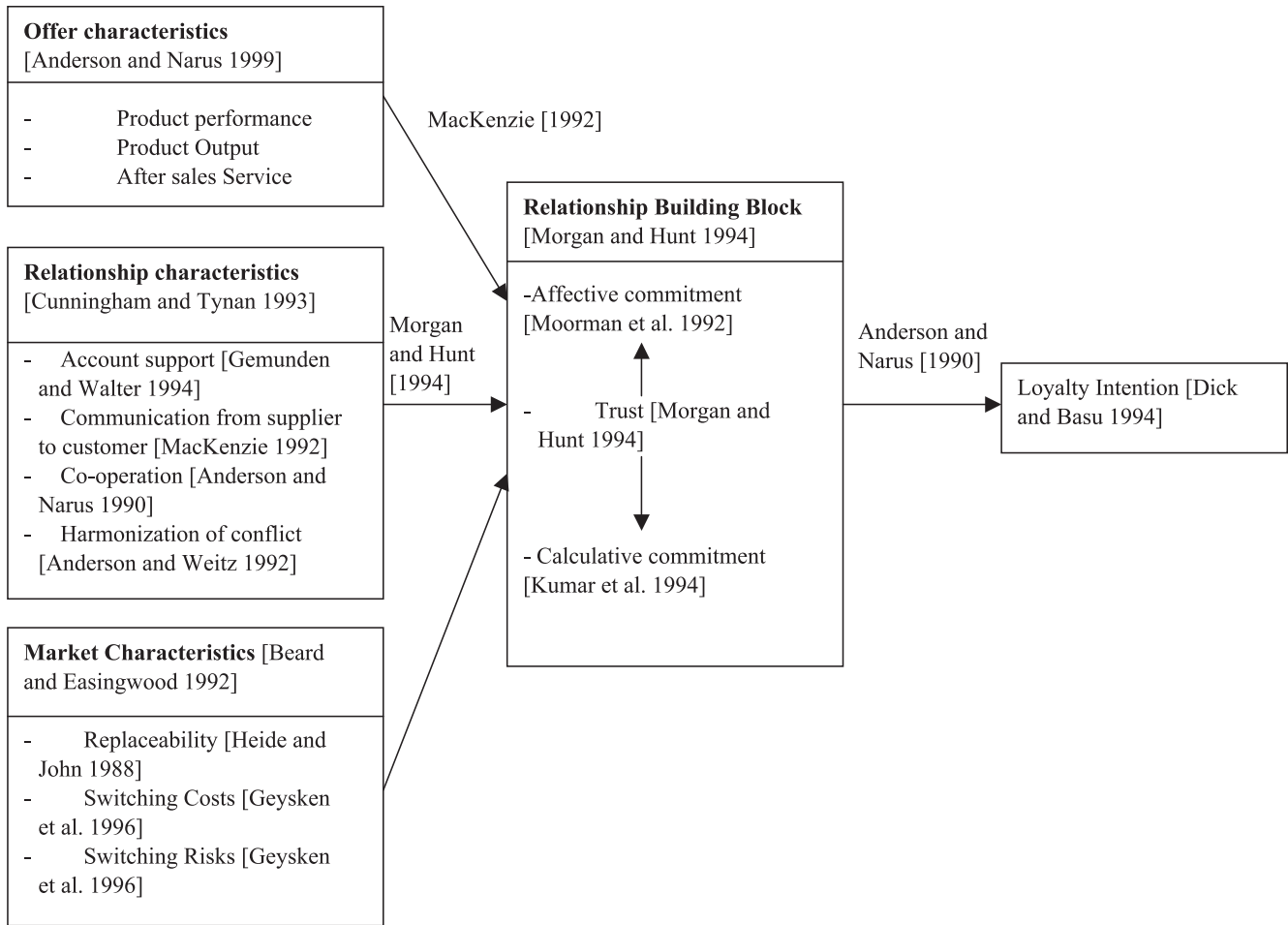[2] Tel.: +31-43-3883739; fax: +31-43-3884918.

Fig. 1. The conceptual model with selected references.

uncertainty. In modeling terms, uncertainty shows up as nondeterministic, that is, probabilistic construct values, parameters, and error terms. It will be argued that this model uncertainty mimics (part of) the uncertainty a real decision maker is confronted with.

Thus, after describing the fundamentals of decision making with the help of structural equation models, the discussion will focus on how the uncertainty component comes in and how it affects the analysis. Next, the results of analysis are presented, followed by a discussion of the implications. Finally, the article concludes with some suggestions for future research.

2. Allocation decisions based on a structural equation model

The results of the model in Fig. 2 can be used to aid in managerial allocation decisions. The idea is that management can influence customers' perceptions of the constructs *offer*, *relationship*, and *market* and hence influence the *intention to stay* of the customer. The basic question is how should management allocate a fixed amount of resour-

ces over these three exogenous constructs in order to achieve the biggest increase in intention to stay?

To fix ideas: Suppose management has resources that when spent completely on improving the offer, the perception of the offer will increase by one point. Similarly, when spent completely on relationships, this construct will increase by one point, or when allocated completely to market that construct will increase by one point. Furthermore, management can also decide to allocate their resources over the three constructs. In that case, the sum of the increases will be exactly one again.

When the model results are considered deterministic, the question raised above is relatively easy to answer, but due to various sources of uncertainty, such interpretation of the estimation results is not very realistic. The first source is the common uncertainty due to model misspecification, measurement errors, and the like. This type of uncertainty is usually accounted for by incorporating error terms. A second source is found in the exogenous constructs. Changes in the measured items are taken as reflecting changes in the latent construct, but this relationship is not exact, reflected by errors in the measurement model. This uncertainty corresponds to the uncertainty related to the
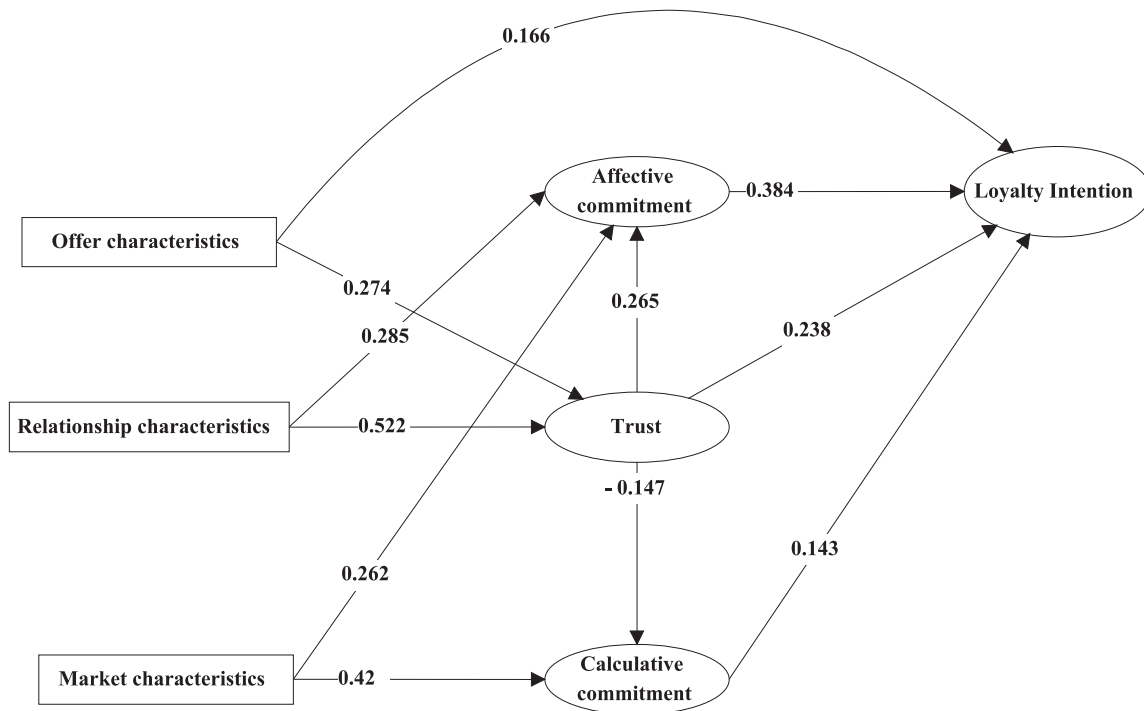
Fig. 2. Empirical model.

manageability of influencing the latent constructs: The assumption is that management is able to influence the perception of these constructs, but this manageability is of an uncertain kind. A final source of uncertainty in the model relates to the parameter estimates. Estimation results are commonly presented as point estimates but basically have the character of a probability distribution. "The" parameter value is nothing else than the expected value of that distribution. Note that although it is natural to speak of uncertainty, the appropriate technical term is risk: The distributions of the nondeterministic elements are known, which typically is a situation of risk.

When the allocation decision is to be made in a situation of risk, management will weigh the expected returns against the risk implied. A simple way to model this is to assume that management holds a utility function, with "return" and "risk" as the variables. Risk is measured in the usual way by the variances or standard deviations of the model outcomes (other risk measures like lower partial moments are discussed by Machina and Pratt, 1997, but since the issue of risk measures is not central in this paper the more traditional measure of variance is applied). When the expected value and the standard deviation of the outcome variables are known (as functions of the allocation), they are put into a utility function and that gives the opportunity to determine the optimal allocation of the budget.

How the various sources of uncertainty can be incorporated in this structural model is the next topic. First, the approach will be illustrated by means of a simple example. Then the analysis will be executed in general format with the help of matrix algebra. After that, it will be shown how

the analysis works out for the estimated model of Fig. 2. Finally, it will be shown how the managerially relevant issue of risk attitude is naturally incorporated in the analysis.

3. Extensive example

The following example will help in catching the ideas put forward in this article. It will also serve as a reference for the upcoming discussion. Note that this example is completely constructed and is not based on any realistic assumptions. The only thing that is realistic is the type of variables chosen.

Assume that an organization can influence the likelihood of clients making a purchase by increasing either the clients' awareness of the organization, or its credibility, or both. An increase of 1 unit in awareness leads to an increase of 0.7 in the likelihood of purchase. An increase of 1 unit in credibility leads to an increase of 0.4 in the likelihood of purchase. Moreover, an increase of 1 unit in awareness also leads to an increase in credibility of 0.5 points.

Awareness and credibility are determined by advertising and attending trade shows, respectively. One million dollars spent on advertising leads to an increase in awareness of 0.3 units. The same amount spent on trade shows leads to an increase of 0.6 units in credibility. This whole story can be summarized in three equations:

$$L = 0.7W + 0.4C \tag{a}$$

$$C = 0.6T + 0.5W \qquad (b)$$

$$W = 0.3A \qquad (c)$$

where L=likelihood of purchase, W=awareness, C=credibility, T=trade shows, and A=advertising. T and A are measured in million dollars, L, W, and C in units. The question is how must the company allocate 1 million dollars over advertising and trade shows in order to maximize the increase in the likelihood of purchase variable.

This is, in fact, not a difficult question, given the model above. Substitute Eq. (c) in (b) and (a), and Eq. (b) in (a); rearrange terms and it becomes immediately clear that

$$L = 0.24T + 0.27A \qquad (d)$$

Hence, spending the complete budget on advertising leads to the greatest return in likelihood of purchases. Advertising is the most effective instrument to increase the likelihood of purchase.

Such a model like Eqs. (a)–(c) above is, however, fraught with uncertainties. These uncertainties for example concern the specification of the model: Are the included variables the only ones that affect each other? Is the assumption of linear relationships realistic? Somewhat similar are uncertainties about the model estimates. Are the given coefficients (0.3, 0.4, etc.) correct?

Such uncertainties translate into uncertainty about the total effect relation (d). Now, assume that when the total budget of 1 million dollars is spent on trade shows, the effect on the likelihood of purchase is still 0.24, but with a variance of 0.06. Similarly, the effect of spending the whole budget on advertising is 0.27, but with variance of 0.09. Thus, Eq. (d) can be complemented by two error terms, one reflecting the uncertainty of the effect of spending in trade shows, the other the uncertainty related to the effect of advertising.

$$L = 0.27T + 0.24A + Te_T + Ae_A \qquad (e)$$

Note that the error terms are multiplied by the amount spent on trade shows and advertising, respectively. Intuitively, this makes sense: When there is only small spending in either one, the (magnitude) of the uncertainty there is accordingly reduced.

Now when the manager seeks to optimize the allocation of the budget, the manager will also take the uncertainty into account. In other words, the manager will optimize some "utility function" with expected return ($E[L]$) and uncertainty, measured by the variance $\text{var}[L]$ as the arguments. As usual the expected values of the error terms are zero; hence the expected return is given by

$$E[L] = 0.24T + 0.27A \qquad (f)$$

The variance is given by

$$\text{var}[L] = T^2\text{var}(e_T) + A^2\text{var}(e_A) \qquad (g)$$

or

$$\text{var}[L] = 0.06T^2 + 0.09A^2$$

where the assumed values for the variances are plugged in. Note that the convenient assumption was made that the error terms are independent, which will not necessarily hold in more complex situations.

To further illustrate the procedure, assume that the manager has the following simple utility function:

$$U = E[L] - \text{var}[L]. \qquad (h)$$

Finally note that the budget of 1 million dollars has to be distributed over T and A. In other words, what is not spent on trade shows is spent on advertising and vice versa, thus, $T=1-A$. Now plugging the expressions for $E[L]$, $\text{var}[L]$, into the utility function, and substituting T with $1-A$ leads, after some straightforward arithmetic, to the following equation:

$$U = 0.18 + 0.15A - 0.15A^2.$$

Maximizing this function leads to A=0.5; hence 50% of the budget is now spent on Trade shows. This simple exercise demonstrates the potential of uncertainty to influence the allocation of budgets.

4. Using the model for allocation decisions under uncertainty

The estimated model of Fig. 2 counts three exogenous variables and four endogenous variables. In matrix notation the model reads:

$$Y = BY + CX + \varepsilon \qquad (1)$$

with Y a vector of length 4 of endogenous variables, X a vector of length 3 with exogenous variables, and ε a vector of length 4 of error terms. B is a 4×4 matrix, and C a 4×3 matrix of parameters. Refer to Fig. 2 for the contents of this model. In the extensive example above, Y would be of length 3 (L, C, and W), X would be of length 2 (T and A), and so forth.

The reduced form of this system is

$$Y = (I - B)^{-1}CX + (I - B)^{-1}\varepsilon \qquad (2)$$

or, alternatively

$$Y = DX + v \qquad (3)$$

with D a 4×3 matrix and v a vector of length 4; D and v are defined by Eqs. (2) and (3), so the expected values of Y and its covariance matrix are

$$E[Y] = E[DX] + E[v] \qquad (4)$$

$$\text{var}(Y) = \text{var}(DX) + \text{var}(v) + 2\text{cov}(DX, v). \qquad (5)$$

As discussed above, stochasticity now enters this model in three ways. First, the error term v has a probability

distribution that can be derived since the distribution of ε is known, as long as **B** is deterministic. Second, the exogenous variables in *X* follow a probability distribution. Finally, the parameters in **D** are functions of parameter estimates and, consequently, also have a probability distribution. For reasons of exposition, the consequences of these three types of uncertainty are next discussed consecutively. Note that in the extensive example above, no distinction was made between the various types of errors: The counterpart of Eq. (5) was simply introduced as Eq. (g).

So, first assume that *X* and **D** are deterministic and suppose that ε has a multivariate normal distribution with mean zero and covariance matrix Σ_ε, which is diagonal. Then υ is also normal with zero mean. Since

$$\upsilon = (I - \mathbf{B})^{-1}\varepsilon \qquad (6)$$

the variance of υ is given by

$$\text{var}(\upsilon) = \text{var}((I - \mathbf{B})^{-1}\varepsilon) = (I - \mathbf{B})^{-1}\Sigma_\varepsilon[(I - \mathbf{B})^{-1}]' \quad (7)$$

as **B** was deterministic. Then the first two moments of *Y* are:

$$\text{E}[Y] = \text{E}[\mathbf{D}X] + \text{E}[\upsilon] = \mathbf{D}X + 0 = \mathbf{D}X \qquad (8)$$

$$\text{var}(Y) = \text{var}(\mathbf{D}X) + \text{var}(\upsilon) + 2\text{cov}(\mathbf{D}X, \upsilon)$$

$$= 0 + \text{var}(\upsilon) + 0 \qquad (9)$$

where var(υ) was given above. Note that the expected value of *Y* depends on *X*, but the variance of *Y* does not depend on *X*. Hence, the allocation of a budget among the elements of *X* does not affect the risk involved. Consequently, maximizing the utility function of the firm in this case simply implies maximizing the expected return.

The next step is to introduce stochasticity in the exogenous variables *X*. In the present context this can be well motivated. The *X*s in the model (offer, relationship, and market) represent theoretical constructs, which have no real counterparts. Instead, they are measured by looking at measurable variables that are supposed to be influenced (determined) by the constructs. This impossibility to measure the constructs makes their true value uncertain. The consequence is that it is not realistic to state with certainty that some exogenous variable increases by one unit, for example. It makes more sense to state that the increase of an exogenous variable is a random variable with expected value one, and a given variance. Thus, a firm may try to influence the value of a construct, but the outcome is uncertain. Assume that this uncertainty is reflected in the variance of the error term in the measurement model.

The error terms in the measurement model are correlated. This means that the covariance matrix of *X*, Σ_X, is not diagonal. The interpretation of this is that when management tries to influence one of the constructs it may simultaneously also influence the value of the other constructs as well.

On the other hand, the errors of the structural model, and of the measurement model are assumed to be independent,

cov(*X*,ε)=0, and consequently, cov(*X*,υ)=0. Now calculating the first two moments of *Y* gives

$$\text{E}[Y] = \text{E}[\mathbf{D}X] + \text{E}[\upsilon] = \mathbf{D}\text{E}[X] \qquad (10)$$

$$\text{var}(Y) = \text{var}(\mathbf{D}X) + \text{var}(\upsilon) + 2\text{cov}(\mathbf{D}X, \upsilon)$$

$$= \mathbf{D}\text{S}_X\mathbf{D}' + \text{var}(\upsilon) \qquad (11)$$

This makes clear that the allocation of the budget enters the utility function of the firm both via the expected value (E[*X*]) and the variance (Σ_X), making a portfolio analysis nontrivial. Nevertheless, the discussion below will illustrate that an analytical solution is still feasible.

Finally, consider the stochasticity resulting from **D**. First, note that it is common to include the variance, resulting from the stochasticity of the parameter estimates, in forecasting in econometrics (Ramanathan, 1995), but also in this structural equations model it is reasonable to consider this variance. The variance of the parameter estimates can be interpreted as an indication of uncertainty about the true parameter values. Uncertainty about the specification of the model is accounted for by the error terms, but even when the model is correctly specified, the uncertainty about the true parameter values, caused, for example, by measurement errors, remains. This may of course have serious consequences for the use of the model. The practical analogy is that decision makers can work with a relationship between two variables that is quantified, but want to take into account how certain they are of the exact numbers in that relationship. Hence, incorporating model uncertainty, by explicitly incorporating the stochasticity of the parameters in deriving forecasts, seems justified.

Consequently, assume that vec(**B**|**C**) (the vector composed of the parameters of the structural equation model, represented by the matrices **B** and **C**) have a multivariate normal distribution with mean vec($\hat{\mathbf{B}}$|$\hat{\mathbf{C}}$) and covariance matrix $\Sigma_{\mathbf{B}|\mathbf{C}}$. It should be clear, however, that this does not lead to tractable formulations for the distribution of **D** or υ any longer. Therefore, an analytical solution is no longer feasible when, simultaneously, stochasticity in both *X*, υ, and **B** and **C** is allowed for. In that case, an alternative approach is available: simulation. Instead of analytically solving the probability distributions of the variables of interest, the probability distributions of these dependent variables are derived by drawing random numbers from the stochastic variables in the model and performing the necessary arithmetic operations with these drawn numbers. The approach is described in full detail in Appendix A.

5. From analytic to simulation results

Working with the simulation results proceeds as follows. First, assume that the firm has resources available so that

when these resources are completely spent on one of the exogenous variables, offer portfolio, relationship portfolio, and market portfolio, the value for that variable will increase by 1 unit. Then calculate the effect of this increase of 1 in each of the exogenous variables in terms of the endogenous variable "intention to stay" only. These effects form the first row of matrix $\mathbf{D}$ above and will be labeled $\boldsymbol{\mu}'$. In the extensive example, this corresponds to the "reduced form" effect of advertising and trade shows, as given in Eq. (d). In the model of Fig. 2, this reduced form defines the return only in terms of the "intention to stay" construct. This is the ultimate variable the firm is interested in, whereas defining the returns in terms of all endogenous variables would unnecessarily complicate the analysis and not contribute to understanding the processes involved.

The next step is to consider how the resources can be optimally allocated among the three exogenous variables to optimize the effect on the intention to stay. In other words, a decision must be made on the weights in the weight vector $\boldsymbol{w}$ that represents the allocation of the budget among the exogenous constructs offer, relationship and market. Obviously the elements of $\boldsymbol{w}$ sum to 1 and are all nonnegative. The weights must be assigned so that some utility function (to be specified by the decision maker), which contains the expected return and the expected risk as its elements, is maximized. Given the linearity of the model it immediately follows that the return can be written as $R=\boldsymbol{w}'\boldsymbol{\mu}$, with $\boldsymbol{\mu}$ the earlier defined vector of total (i.e., direct plus indirect) effects of each X on Y.

The effect of introducing risk has been demonstrated in the extensive example above. The effect for the current model is illustrated in Table 1, where the optimal budget allocation (the weights) in the cases without, and with equal risk associated with the three exogenous variables, are given. Similar to the extensive example, introducing risk leads to a larger spread in the portfolio, obviously at the cost of expected return, but at the benefit of a lower variance in the outcome variable.

For the sake of arithmetically including risk in the budget allocation decisions, complete estimation results of the model are given in Appendix B, including the estimated covariance matrices.

Stochasticity in the error term only gives $\mathrm{E}[Y]=\mathbf{D}w$ and consequently $\mathrm{E}[y_1]=0.264w_1+0.262w_2+0.160w_3$, and $\mathrm{Var}(y_1)=\mathrm{var}(v)=0.708$, independent of the weights as was discussed before. Referring to the analysis above, it still

holds that the optimal allocation of the budget is to spend it entirely on the offer portfolio. The offer portfolio gives highest returns, whereas the risk is independent of the allocation of the budget.

With stochasticity in the exogenous variables, the problem becomes more complex, but still an analytic solution is feasible. Referring to the earlier discussion [see Eq. (10)], the expected return is still the same,

$$\mathrm{E}[y_1] = \boldsymbol{\mu}'\boldsymbol{w} = 0.264w_1 + 0.262w_2 + 0.160w_3 \qquad (12)$$

However, the risk is more involved as $\mathrm{var}(Y)=\mathbf{D}\Sigma_X\mathbf{D}'$. Define $\mathbf{W}$ as the diagonal matrix with the weights of $\boldsymbol{w}$ as its diagonal elements and 0s else, so that $\boldsymbol{w}=\mathbf{W}i$, $i=(1,1,1)'$. Then:

$$\mathrm{var}(y_1) = \boldsymbol{\mu}'\mathbf{W}\Sigma_X\mathbf{W}'\boldsymbol{\mu} + \mathrm{var}(\boldsymbol{v}) = 0.0697w_1^2 + 0.0686w_2^2$$
$$+ 0.0256w_3^2 + 0.0761w_1w_2 + 0.0169w_1w_3$$
$$+ 0.0253w_2w_3 + 0.708. \qquad (13)$$

Solving the portfolio problem, assuming the utility function is $U(R,S)=R-S$ like above, the optimal solution becomes: $w_1=0.569$, $w_2=0.577$ and $w_3=-0.146$. Note, however, that this solution is infeasible because a weight cannot be negative. A feasible solution can be obtained by fixing $w_3=0$ and again solving the problem. With that additional constraint, the solution becomes $w_1=0.507$, $w_2=0.493$, which means that the budget should be allocated approximately equally to the offer portfolio and the relationship portfolio.

Finally, consider the introduction of stochasticity in the parameters of the model. As noted above, an analytical solution is no longer feasible, since the distribution of the return and risk, as a function of the weights is too complex, and hence the simulation approach is applied. This means that random numbers are drawn for all stochastic elements in the model, that is, the Xs and the elements of $\mathbf{D}$. The Xs are assumed to have a multivariate normal distribution with expected value $(1,1,1)$ and covariance matrix as given in Appendix B. The elements of $\mathbf{D}$ similarly follow a multivariate distribution as defined in that appendix. The calculated first two moments of the resulting distribution are given in Table 2, based on a random drawing of 1000 numbers as described in Appendix A.

The table shows, comparable to Table 1, that spending the whole budget on improving the offer would lead to an expected increase of .274 in the intention to stay variable, with a standard deviation of .442, and so forth.

Using the results of Table 2, now the expected return is

$$\mathrm{E}[y_1] = 0.274w_1 + 0.258w_2 + 0.163w_3 \qquad (14)$$

Table 1
Introducing risk in the allocation model

		Optimal weight without risk	Optimal weight with equal risk
Return on offer	0.264	1	0.404
Return on relationship	0.262	0	0.400
Return on market	0.160	0	0.196

Table 2
Simulation results with all uncertain elements stochastic

	Mean	S.D.	Covariances			Correlations		
Ret on O	.274	.442	.196	.049	.013	1	.324	.124
Ret on R	.258	.342		.117	.014		1	.177
Ret on M	.163	.235			.055			1

and the associated risk

$$\text{var}(y_1) = 0.196w_1^2 + 0.117w_2^2 + 0.055w_3^2$$

$$+ 0.098w_1w_2 + 0.026w_1w_3 + 0.028w_2w_3. \quad (15)$$

Solving once again the maximization problem with $U=R-S$ gives the solution: $w_1=0.273$, $w_2=0.469$, and $w_3=0.258$. Therefore, with this uncertainty included, also the market portfolio should receive its share. Moreover, the relationship portfolio has become the most important portfolio. This compares to the extensive example in which the introduction of risk led to a spread in the allocated budget.

6. Some experimentation with the allocation decision framework

It is obvious that the results depend significantly on the choice of utility function. In this respect it is interesting to investigate how the risk attitude influences the optimal allocation decision. This risk attitude defines the relative weights attached to return (R) and risk (S) in the utility function. The more risk averse, the greater the weight put on S.

Risk aversion can be incorporated in the linear function as used above, by weighing the S variable with a coefficient β: $U(R,S)=R-\beta S$. In this case, $\beta>0$ is the measure of risk aversion, with high values for β corresponding to large risk aversion. The goal is to define the weights w_1, w_2, and w_3 expressed as functions of β. Hence, a solution for the following allocation problem is sought:

$$\text{Max } R - \beta S \quad (16)$$

$$\text{s.t. } R = \boldsymbol{w}'\boldsymbol{\mu} \quad (17)$$

$$S = \boldsymbol{w}'\boldsymbol{\Sigma}\boldsymbol{w} \quad (18)$$

$$\boldsymbol{w}'i = 1 \quad (19)$$

$i=(1,1,1)'$ and the last condition says that the weights sum to 1.

Solving this problem with Lagrange multiplier method leads to the following quite tedious expression for $\boldsymbol{w}$:

$$\boldsymbol{w}' = \left(\frac{\left(\frac{2\beta + \boldsymbol{\mu}'\mathrm{S}^{-1}i}{i'\mathrm{S}^{-1}i} \right)i - \boldsymbol{\mu}}{2\beta} \right)\mathrm{S}^{-1} \quad (20)$$

Substituting $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ with the values in Table 2 gives the more down-to-earth expressions for w_1, w_2, and w_3:

$$w_1 = 0.109 + 0.164/\beta \quad (21)$$

$$w_2 = 0.226 + 0.242/\beta \quad (22)$$

$$w_3 = 0.664 - 0.406/\beta \quad (23)$$

Note that for every value of β the sum of w_1, w_2, and w_3 indeed equals 1, and that for $\beta=1$ the solution that was presented in Table 1 is again found. Note, however, that when $\beta<0.611$ (=0.406/0.664) w_3 becomes negative, which implies an infeasible solution. For that range of values for β set $w_3=0$ and solve the optimization problem again. This leads to:

$$w_1 = 0.316 + 0.037/\beta \quad (24)$$

$$w_2 = 0.684 - 0.037/\beta \quad (25)$$

Hence, when $\beta<0.054$, w_2 becomes negative, and setting $w_2=0$ as well for that range of β values gives $w_1=1$. All this can be depicted graphically; see Fig. 3, showing the solutions in w_1-w_2 space.

In this figure the line $w_1 + w_2 = 1$ defines those solutions for which $w_3=0$. Going from this line into the direction of the origin implies that w_3 increases, so this diagram makes it clear that increased risk aversion (larger β) means giving more weight to w_3 and also to w_2, relative to w_1. This means that the more risk averse the managers are, the more attention they should pay to the market conditions. On the other hand, when β becomes small, that is, risk proneness increases, the whole budget should be spent on the offer itself.
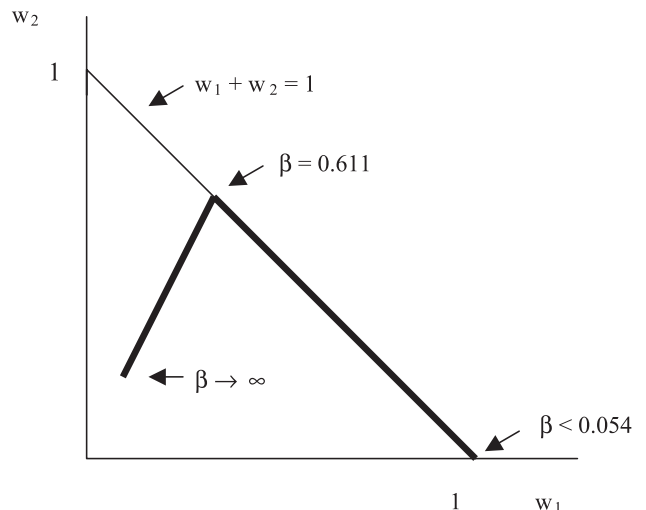

Fig. 3. Allocation of a budget as a function of risk aversion.

7. Discussion

For decision makers, direct input–output or cause-and-effect models like market response models (Lilien & Rangaswamy, 1998) are often a sufficient tool. The analytical understanding is left in the black box of the model. Structural equation models quite in contrast seek to get hold of that black box, thereby gaining in rigor and depth of understanding. These characteristics of SEM should help in getting the models accepted by the decision makers, and this paper shows that they can also provide support in the decision-making process.

One aspect in particular needs to be emphasized. SEMs are well suited to make explicit the type of uncertainty that is incorporated. Therewith they make it possible to quantify the degree of uncertainty, simultaneously leaving the option open that uncertainties can be interrelated. The estimated covariance structure in the measurement model and the structural model give this opportunity.

The model that was used in this paper to demonstrate the approach indicates the usefulness of SEM in decision making. The calculations above clearly exemplify the type of advice on investment decisions that can be derived from the analysis demonstrated in this paper. This could read as follows:

> The higher risk-averse managers are, the more they are advised to invest in the market positioning and relationships. In contrast, risk-prone managers probably will be better-off investing in product innovations. This conclusion is certainly valid for the short term, but might be valid on the longer term as well because of the shown loyalty of the customer base. The importance of relationship management is intermediate. The extremely risk prone manager only looks at the offer. The extreme risk-averse manager looks mainly at the market conditions. In between, the importance of relationships reaches a maximum. This means that moving along the continuum from risk prone to risk averse the manager first starts looking at his most direct environment, his relationships, but at some point recognizes that this is not enough, and that he should also look at the other actors in the market.

8. Limitations and suggestions for prospective research

Demonstrating the feasibility of the decision-making approach required several simplifying assumptions. Trying to relax these assumptions will lead to more general and therefore more realistic and useful outcomes. On the technical side, the strongest assumption was that of a linear utility function in returns and risk only. More general assumptions should be investigated. Related to that is the adopted, simplistic concept of risk aversion. Arrow (1970) has defined risk aversion as a property (or result) of a chosen utility function rather than plugging in a coefficient that reflects risk aversion.

Another assumption was that for each of the exogenous constructs, increasing the score by one point would cost the same. This is hardly realistic; on the other hand, establishing such (quantitative) relationships is a matter of thorough market research. Once such relationship is established, this can easily be incorporated in the optimization model as a budget restriction. In fact, the currently applied restriction on the weight factor and such budget restriction are technically the same.

A more fundamental issue is the assumption of linearity: when it costs 1 dollar to reach an increase of one point, 2 dollars will lead to an increase of two points. Although this is an implication of the estimated structural equations model, it presumably is far from reality. For one thing, the applied measurement scales have fixed limits of 1 and 7. Consequently, it is advisable to accept that only marginal changes stay within the acceptable region of meaningful outcomes, defined by the model assumptions.

All these limitations themselves give opportunities for further research. The most important achievement of this paper is its attempt to support rational decision making based on an estimated structural model. Definitely, the appropriateness of the model is crucial to the suitability of the approach, but for this study was considered as a starting point. Given this starting point, the approach offers opportunities to investigate how decisions will change when assumptions or parameters (like the risk-aversion parameter β in this article) will be adapted. This sensitivity analysis could be extremely helpful for understanding the implications of decisions based on models.

Acknowledgements

Appendix A. Simulating the distribution of Y

When the analytic distribution of a random variable cannot be derived, it can be approximated by simulation. In this particular case, Y is a moderately complicated function of a number of random variables, for all of which the (multivariate) distribution is known. Then the distribution of Y can be approximated by drawing random numbers from all the distributions of the random variables that define Y and calculate the simulated distribution of Y.

Drawing random numbers is highly mechanized in many statistical software packages and even in a number of spreadsheets. However, this is mainly restricted to drawing random numbers from uniform distribution and some other

univariate distributions like the normal, exponential, and others. Simulating multivariate distributions is more complicated. The general approach to simulate multivariate distributions is based on the following fundamental relationships in statistics:

$$P(a,b) = P(a|b)P(b)$$

where $P(a,b)$ is the multivariate (here, bivariate) probability of a and b, $P(a|b)$ is the conditional probability of a, given b, and $P(b)$ is the marginal probability of b. This rule also holds for the distributions:

$$f(a,b) = f(a|b)f(b)$$

where the fs indicate the distribution functions and the rest is analogous. Since b can itself be a composite random variable, a generalization to really multivariate (more than 2) variables is straightforward. For example, let b in the expressions above be the composite random variable c and d, then the expression becomes

$$P(a,c,d) = P(a|c,d)P(c,d) = P(a|c,d)P(c|d)P(d)$$

where the last equality should be obvious.

Hence, a multivariate distribution can normally be decomposed into the product of a number of conditional distributions and a marginal distribution. This result can subsequently be used to simulate the distribution of the simultaneous random variables, in particular these marginal and conditional distributions are known (see, e.g., Nijkamp, Oosterhaven, Ouwersloot, & Rietveld, 1992; Rietveld & Ouwersloot, 1992). Referring to the equation above, the idea is to first draw a number for d, say d^*, substitute this particular d^* in the otherwise known distribution of c, conditional on $d=d^*$. Next, draw a number c^* from this now completely specified distribution of c and substitute both c^* and d^* in the distribution of a, conditional on $c=c^*$ and $d=d^*$. Finally draw a random number for a, say a^*. Now a^*, c^*, and d^* constitute a random drawing from the multivariate distribution of a, c, d.

When the multivariate distribution is normal, that is, a, c, and d follow a multivariate distribution with expectation μ and variance Σ, simulating the simultaneous distribution in the way described above is relatively simple. The marginal distribution of the first variable in this case is univariate normal, the conditional distribution of the second, given the first, is again univariate normal, and so forth.

To be more precise, suppose that x_1 to x_n have a multivariate distribution with $E(\mathbf{x})=(\mu_1, \ldots, \mu_n)'$, and $var(\mathbf{x})=\Sigma$ with elements σ_{ij}. The marginal distribution for each x_i then is a univariate normal distribution with $E(x_i)=\mu_i$ and $var(x_i)=\sigma_{ii}$. To define the conditional distribution of $x_1, \ldots, x_k$, given $x^*_{k+1}, \ldots, x^*_n$ partition the covariance matrix as

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$

where Σ_{11} is the covariance matrix of the first k variables, and so forth. Assuming that the vector of expected values is similarly partitioned the mean of the conditional distribution of $x_1, \ldots, x_k$ given $x^*_{k+1}, \ldots, x^*_n$ is (Johnson & Wichern, 1998):

$$E(x_1,\ldots,x_k|x_{k+1} = x^*_{k+1},\ldots,x_n = x^*_n)$$
$$= E(x_1|x_2 = x^*_2) = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x^*_2 - \mu_2)$$
$$cov(x_1|x_2 = x^*_2) = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

Consequently, this gives a well-defined and completely specified distribution function for each x_i that can be used for a random drawing using standard random number generators.

Applying this procedure to the stochastic variables in our model facilitates the calculation of the simulated variable y_1, "intention to stay." Repeating this procedure a large number of times (say, 1000 or so) gives a simulated distribution function for Y.

Appendix B. Estimation results from De Ruyter et al. (2001)

The estimation results that are used for the simulations are taken from De Ruyter et al. (2001). These estimates and the necessary covariance matrices are presented here.

The point estimators and the corresponding variances of the parameter matrices **B** and **C** are as follows:

B=	0	0.384	0.237	0.145	Variances	*	0.200	0.212	0.184
	0	0	0.288	0		*	*	0.217	*
	0	0	0	0		*	*	*	*
	0	0	−0.142	0		*	*	0.207	*
C=	0.167	0	0		Variances	0.202	*	*	
	0	0.264	0.258			*	0.219	0.192	
	0.296	0.491	0			0.197	0.197	*	
	0	0	0.417			*	*	0.207	

All parameter estimates are assumed uncorrelated, hence it suffices to only report the variances.

The errors of the estimated relations are also all assumed uncorrelated. Only the variances enter the analysis. The estimated variances of the respective equations, that is, the diagonal elements of the matrix Σ_ε, are as follows:

Intention to stay	0.546
Affective commitment	0.607
Trust	0.511
Calculative commitment	0.830

The errors of the measurement model of the exogenous variables, on the other hand, are correlated. Their correlation matrix Σ_X is as follows:

Offer portfolio	1		
Relationship portfolio	.550	1	
Market portfolio	.200	.302	1

This matrix is applied in the analysis as if it were the covariance matrix. This basically implies that an expected change of one unit in an exogenous variable is associated with a variance of 1, and the above reported covariances. This variance is probably unrealistically large. However, the qualitative aspects of the analysis are unaffected by this assumptions, whereas the exposition of the approach is facilitated.

References

Anderson, E. W., & Weitz, B. (1992). The use of pledges to build and sustain commitment in distribution channels. *Journal of Marketing Research*, *29*, 18–34.

Anderson, J. C., & Narus, J. A. (1990). A model of distributor firm and manufacturer firm working partnerships. *Journal of Marketing*, *54*, 42–58.

Anderson, J. C., & Narus, J. A. (1999). *Business market management*. Upper Saddle River, NJ: Prentice Hall.

Arrow, K. J. (1970). *Essays in the theory of risk bearing*. Chicago: Markham.

Cunningham, C., & Tynan, C. (1993). Electronic trading inter-organizational systems and the nature of buyer–seller relationships: The need for a network perspective. *International Journal of Information Management*, *13*, 3–28.

De Ruyter, K., Moorman, L., & Lemmink, J. (2001). Antecedents of commitment and trust in customer–supplier relationship in high technology markets. *Industrial Marketing Management*, *30*, 255–269.

Dick, A. S., & Basu, K. (1994). Customer loyalty: Toward an integrated conceptual framework. *Journal of the Academy of Marketing Science*, *22*, 99–113.

Gemunden, H. G., & Walter, A. (1994). The relationship-promoter: Key person for interorganizational innovation co-operation. In J. N. Sheth, & A. Parvatiyar (Eds.), *Relationship marketing: Theory, methods and applications*. Atlanta: Proceedings of the 2nd Research Conference on Relationship Marketing (pp. 1–15). Atlanta, GA: Emory University.

Geyskens, I., Steenkamp, J. -B. E. M., Scheer, L. K., & Kumar, N. (1996). The effects of trust and interdependence on relationship commitment: A trans-Atlantic study. *International Journal of Research in Marketing*, *13*, 303–318.

Heide, J. B., & John, G. (1988). The role of dependence balancing in safeguarding transaction-specific assets in conventional channels. *Journal of Marketing*, *52*, 20–35.

Johnson, R. A., & Wichern, D. W. (1998). *Applied multivariate statistical analysis*. Upper Saddle River, NJ: Prentice Hall.

Kumar, N., Hibbard, J. D., & Stern, L. W. (1994). *The nature and consequences of marketing channel intermediary commitment* (Report No. 94-115). Cambridge: Marketing Science Institute.

Lilien, G. L., & Rangaswamy, A. (1998). *Marketing Engineering*. Reading, MA: Addison Wesley.

Machina, M. J., & Pratt, J. W. (1997). Increasing risk: Some direct constructions. *Journal of Risk and Uncertainty*, *14*, 103–127.

MacKenzie, H. F. (1992). *Partnering attractiveness in buyer–seller relationships*. Unpublished PhD thesis, University of Western Ontario, Canada.

Moorman, C., Zaltman, G., & Deshpandé, R. (1992). Relationships between providers and users of marketing research: The dynamics of trust within and between organizations. *Journal of Marketing Research*, *29*, 314–329.

Morgan, R. M., & Hunt, S. D. (1994). The commitment–trust theory of relationship marketing. *Journal of Marketing*, *58*, 20–38.

Nijkamp, P., Oosterhaven, J., Ouwersloot, H., & Rietveld, P. (1992). Qualitative data and error measurement in input–output analysis. *Economic Modeling*, 408–418.

Ramanathan, R. (1995). *Introductory econometrics*. Fort Worth, TX: Dryden Press.

Rietveld, P., & Ouwersloot, H. (1992). Ordinal data in multicriteria decision making, a stochastic dominance approach to sitting nuclear power plants. *European Journal of Operational Research*, *56*, 262–294.

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