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Market-based capabilities, perceived quality and firm performance

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Chapter 5

The Effect of Strategic Marketing Capabilities on Firm Performance: A Bayesian Linear and Nonlinear Latent Variable Analysis

Abstract In the previous chapter, an integrated model of marketing, linking the relationship marketing perspective to the market orientation direction, is proposed. In this chapter, we develop a conceptual framework to assess the value of a firm's strategic marketing capabilities. The framework proposes that strategic marketing capabilities contribute to the financial performance of the firm. Besides a linear effect, we also investigate a nonlinear relationship using latent variable modeling. In doing so, we utilize a Bayesian approach to estimate the proposed linear and nonlinear latent variable models. Results support the notion that firms possessing strategic marketing capabilities are more likely to generate higher firm performance. The findings also demonstrate the contingent nature of the influence of strategic marketing capabilities on firm performance. Surprisingly, results show that two combinations of strategic marketing capabilities have negative effects on the financial performance of the firm. The findings of this study contribute to theory in marketing strategy and have important implications for firms.

5.1 Introduction

Although the assertion that marketing capabilities influence a firm's financial performance is often recognized, researchers tend to adopt one of two approaches to examining competitive advantage: a focus on the market (market orientation) or a focus on relationships (relationship marketing). Although these influences on performance have been examined in isolation, they have not explicitly been investigated in an integrated framework.

In the previous chapter we develop an integrated model, denoted the strategic marketing capabilities construct, incorporating both market-driven and market-relating components. The rationale to integrate these two perspectives is given by several strategic marketing scholars (e.g., Day, 1994; Day and Wensley, 1988; Peteraf and Bergen, 2003; Srivastava, Shervani and Fahey 1998, 1999). Applying factor analytical methods, support is found for this model. The development of this model enables us to examine the following question, which is evident for business practitioners seeking to develop and leverage marketing capabilities: what is the actual effect of strategic marketing capabilities on firm performance? Furthermore,

the identification of which combination of strategic marketing capabilities should be leveraged remains largely unexplored in the marketing literature.

Since the strategic marketing capabilities construct represents a hierarchical factor model, structural equation modeling is the preferred approach to assess the contribution of strategic marketing capabilities to the financial performance of the firm. Building on prior research, we propose two models: (1) a main effects model, and (2) an interaction effects model. Estimating a main effects model using latent variable modeling is *straightforward*. Concerning models with interaction terms of latent variables several approaches have been proposed in the literature. In general, the product indicator method (Kenny and Judd, 1984) is used to analyze models with interaction terms of latent variables. However, psychometric research indicates several methodological problems when implementing interactions in latent variable models using traditional methods (Jöreskog and Yang, 1996). Recently, Lee et al. (2004) demonstrate that the Bayesian approach is in general better than the product indicator approach in determining interaction effects. Since recent statistical literature suggests the superiority of the Bayesian latent variable modeling in deriving the correct estimates (see for example, Arminger and Muthen, 1998; Lee et al., 2004), we use Arminger and Muthen's (1998) approach in estimating the linear and nonlinear latent variable model. Furthermore, we discuss and apply Gelfand and Ghosh's (1998) decision-theoretic model selection criterion, which is based on the posterior predictive loss approach.

With this study we aim to make the following contributions. First, we investigate the relationship between strategic marketing capabilities and firm performance. Furthermore, we use a Bayesian approach to the proposed latent variable models to obtain correct estimates. Also, we describe and apply the Gelfand and Ghosh criterion, to compare the two models (main effects and interaction effects model) under investigation.

This chapter is organized as follows. In the next section, we discuss our conceptual framework and hypotheses. After that, methodological issues are described in detail. Finally, we test our framework in the electrotechnical wholesale sector in the Netherlands using both linear and nonlinear latent variable models and discuss the outcomes.

5.2 Conceptual Framework and Hypothesis

In the previous chapter we integrate the 'relational view of competitive advantage' to a 'market-driven view of competitive advantage' (see for the latter, Dyer and Singh (1998)) and propose and validate the strategic marketing capabilities construct. In this chapter we develop a conceptual framework to assess the contribution of strategic marketing capabilities to a firm's financial performance. In accordance with the marketing concept (Drucker, 1954; Narver and Slater, 1990)), the conceptual framework links the strategic marketing capabilities directly to firm performance. Furthermore, in line with Day's (1994) thesis, we estimate a model suggesting interaction between the market-driven and market-relating capabilities

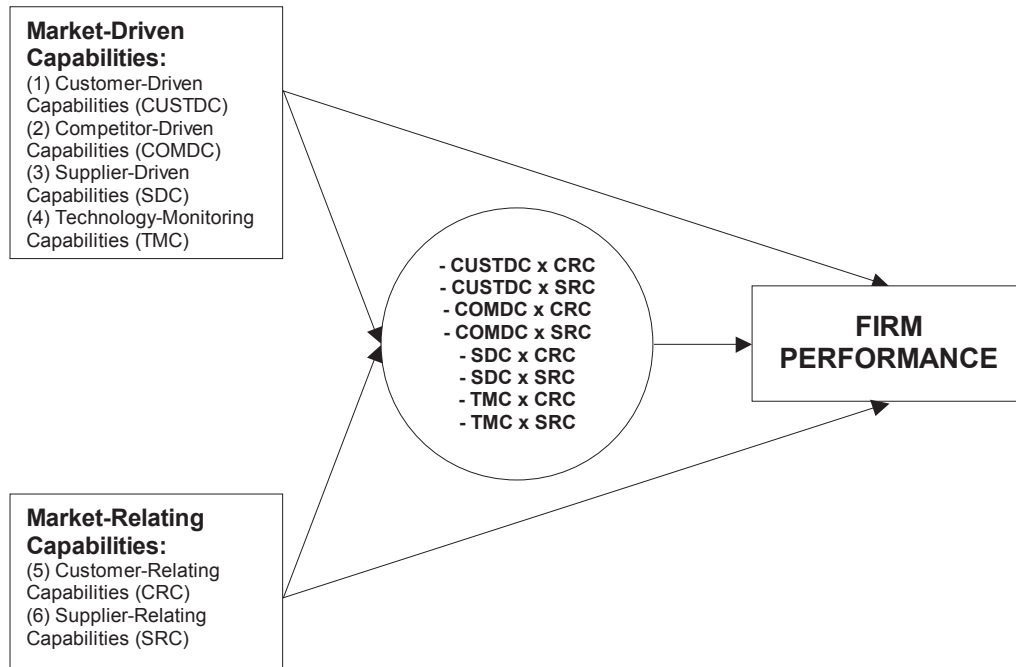


Figure 5.1: Conceptual Framework

in determining firm performance. Figure 5.1 depicts the proposed framework. First, we begin by reviewing the literature suggesting a main effect of strategic marketing capabilities on business performance. Thereafter, we deal with some literature proposing a synergistic effect of various strategic marketing capabilities on firm performance.

5.2.1 Strategic Marketing Capabilities and Financial Performance: The Case of a Linear Relationship

Early work in the field of the marketing concept largely suggests a ‘profit orientation’ as part of the marketing concept (McNamara, 1972). Recently, profitability is seen as a consequence of market-oriented behavior, rather than a component of this concept (Kohli and Jaworski, 1990). Felton (1959) states that the basic purpose of the marketing concept is to produce “maximum long-range corporate profits” (p. 55).

Superior firm performance as a consequence of market orientation, is widely supported in the literature (e.g., Cano, Carrillat and Jaramillo, 2004; Narver and Slater, 1990; Pelham and Wilson, 1996; Reukert, 1992; Deshpande and Farley, 1998; Deshpande et al., 1993). For example, Slater and Narver (1994) find significant influences of market orientation on new product success, sales growth and return on investment. Furthermore, two recent meta analyses (Cano et al., 2004; Kirca, Jayachandran and Bearden, 2005) demonstrate that market-based behavior has a

positive impact on firm performance.

Increasingly, suppliers derive value from being part of one or more organizational networks. As firms increasingly become the node in an interconnected web of formal and informal relationships, their capacity to generate, integrate and leverage knowledge extends considerably beyond the resources they own and control. Findings about the financial benefits of relational ties, both with suppliers and customers, are impressive (Heide and John, 1992; Johnson and Selnes, 2004; Gulati, 1998; Kalwani and Narayandas, 1995; Lee, So Tang 2000; Selnes and Sallis, 2003). For example, Gavirneni, Kapuscinski and Tayur (1999) study the influence of partial and complete information sharing in a supplier-retailer setting, and also compare these to a base case of no information. Their experimental results show that the optimal policy in a model with additional information performs better than the optimal policy in a model with restricted information.

In summary, our first hypothesis specifies the relationships between the six building blocks of strategic marketing capabilities and firm performance. This model is in line with Noble et al.'s (2002) perspective that it is myopic to assume that only one strategic resource or orientation is the only legitimate guiding model for firm success. Therefore,

hypothesis 1 the higher the firm's (a) customer-driven capabilities, (b) competitor-driven capabilities, (c) supplier-driven capabilities, (d) technology-monitoring capabilities, (e) customer-relating capabilities, and (f) supplier-relating capabilities, the higher the financial performance of the firm.

5.2.2 Strategic Marketing Capabilities and Firm Performance: The Case of a Nonlinear Relationship

Although a direct main effect between various components of strategic marketing capabilities and firm performance is frequently suggested and examined, research investigating a nonlinear effect (in the parameters) is relatively scarce. Thus relatively little is known about the existence and sign of an interaction effect between the dimensions of strategic marketing capabilities and firm performance. A fundamental question is whether the impact of market-driven capabilities on firm performance is enhanced by market-relating capabilities. Investigating the interaction between market-driven and market-relating components is important. First, some recent literature in strategic marketing explicitly defend a contingency approach in investigating marketing models (Day and Van den Bulte, 2002; Rindfleisch and Moorman, 2003; Slotegraaf, Moorman and Inman 2003). Second, examining possible moderators for market-based behavior is frequently recommended (Baker and Sinkula, 1999). An additional reason to investigate an interaction effects model relates to the mixed results of empirical studies relating market orientation (as a set of values) to firm performance (e.g. Moorman and Rust, 1999; Noble, Sinha and Kumar, 2002).

In summary, we model the interactions among several dimensions of strategic marketing capabilities and relate them to firm performance. In modeling the inter-

actions, we only consider two-way interactions. Although higher-order interactions may have a significant effect on the dependent variables, we do not explore these effects because of our rather small sample size and the complexity of a higher-order model. So, we hypothesize that

hypothesis 2 the firm's performance is positively affected by the interaction between (a) customer-driven capabilities (CUSTDC) and customer-relating capabilities (CRC), (b) CUSTDC and supplier-relating capabilities (SRC), (c) competitor-driven capabilities (COMDC) and CRC, (d) COMDC and SRC, (e) supplier-driven capabilities (SDC) and CRC, (f) SDC and SRC, (g) technology-monitoring capabilities (TMC) and CRC and TMC and SRC.

5.3 Method

5.3.1 Samples and Measurement

The sampling frame is a list of 843 technical wholesalers in the Netherlands. As described in chapter 2, we sent questionnaires to these wholesalers, including a cover letter, explaining the study goal and a stamped return envelope to the owner or manager of each firm. Of these 843 surveys, 137 are returned.

Details on the strategic marketing capabilities construct are given in chapter 4. Briefly, the measures for the first three factors in this model, customer-driven, competitor-driven and supplier-driven capabilities are derived from studies in market orientation (Kohli and Jaworski, 1990; Langerak, 2001; Narver and Slater, 1990). Items for the technology-monitoring capabilities scale are derived from Srinivasan et al.'s (2002) study. Concerning customer-relating and supplier-relating capabilities, we use several sources to infer our items (Buvik and John, 2000; Doney and Cannon, 1997; Lusch and Brown, 1996). In this study, we further purify the construct introduced in the previous chapter (see Appendix D)

We measure wholesale firm performance on five aspects of efficiency and productivity: sales growth, profit growth, overall profitability, labor productivity and cash flow. These are all measured on a seven-point Likert scale, where 1 = "strongly disagree" and 7 = "strongly agree."

5.3.2 Structural Equation Modeling

The structural equation modeling approach involves two conceptually distinct models. First, a measurement model that relates measured variables to unmeasured variables, often denoted as latent factors, is specified. Second, a latent variable model that relates latent factors to each other is specified and estimated.

Confirmatory Factor Analysis

Since the latent variables are exogenous or endogenous to the model, the literature often makes a distinction between: (1) a measurement model for the exogenous

variables, and (2) measurement model for the endogenous variables. The exogenous variables model may be expressed as

$$x = \Lambda_x \xi + \delta \quad (5.1)$$

where x represents a vector of $q \times 1$ observed variables; Λ is a $q \times n$ factor loadings matrix, that relates n factors to q observed variables; ξ is a vector of $n \times 1$ latent variables; δ is a $q \times 1$ vector of measurement error in x . The measurement model for the endogenous variables may be presented as

$$y = \Lambda_y \eta + \varepsilon \quad (5.2)$$

where y represents a vector of $q \times 1$ observed variables; Λ is a $q \times n$ factor loadings matrix, that relates n factors to q observed variables; η is a vector of $n \times 1$ latent variables; ε is a $q \times 1$ vector of measurement error in y .

The Linear Latent Variable Model

A structural model for latent variables is focused on studying the relationship among latent variables, η and ξ and may be expressed as

$$\eta = \mathbf{B}\eta + \Gamma\xi + \zeta \quad (5.3)$$

where the \mathbf{B} matrix indicates the relationship between latent variables in η , the matrix Γ describes the influence of ξ on η and the ζ vector is the unexplained part of η . Several assumptions underly this model.¹ In the next equations, it will be shown that equation 5.3 can be rewritten to a linear regression model. Having the structural model

$$\eta - \mathbf{B}\eta = \Gamma\xi + \zeta \quad (5.4)$$

and assuming that the inverse of matrix $(\mathbf{I} - \mathbf{B})$ exists, we obtain a linear model

$$\begin{aligned} (\mathbf{I} - \mathbf{B})\eta(\mathbf{I} - \mathbf{B})^{-1} &= (\mathbf{I} - \mathbf{B})^{-1}\Gamma\xi + (\mathbf{I} - \mathbf{B})^{-1}\zeta \\ \eta &= (\mathbf{I} - \mathbf{B})^{-1}\Gamma\xi + (\mathbf{I} - \mathbf{B})^{-1}\zeta = \Pi\xi + \zeta^* \end{aligned} \quad (5.5)$$

¹We refer to Bollen (1989) for further details about these statistical assumptions.

where $\Pi = (\mathbf{I} - \mathbf{B})^{-1}\Gamma$ and $\zeta^* = (\mathbf{I} - \mathbf{B})^{-1}\zeta$. This reduced structural model may be seen as a multivariate regression equation² of latent variables η on ξ , where Π represents the coefficient. Taking the factor models into account, the variance-covariance matrix, defined as Σ , becomes

$$\Sigma = Y(\theta) \tag{5.6}$$

where θ are the parameters to be estimated; usually the parameters Ω , Φ , Ψ , Λ_x , Θ_δ , Λ_y and Θ_ε .

The Nonlinear Latent Variable Model

We introduce a nonlinear version of the SEM model. In doing so, we largely follow Arminger and Muthén's (1998) approach. Let ξ be a vector of random variables that is multivariate normal with $\xi \sim N(0, \Phi)$. Let $\beta = f(\xi)$ a deterministic function of ξ , which is known. A linear regression model connects η with β

$$\eta = \Omega\beta + \zeta \tag{5.7}$$

where $\zeta \sim \mathcal{N}(0, \Psi)$ is a disturbance term, Ω is a matrix of regression coefficients of η on β . Note that this model is linear in the parameters, but nonlinear in the components of ξ . The variables ξ and η are connected to observed variables x and y with the measurement models

$$x = \Lambda_x\xi + \delta, \quad \delta \sim \mathcal{N}(0, \Theta_\delta) \tag{5.8}$$

$$y = \Lambda_y\eta + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \Theta_\varepsilon) \tag{5.9}$$

A special case of this model is a model that allows for interactions of latent variables ξ with a univariate dependent variable

$$\beta_i = (\xi_{i1}, \dots, \xi_{im}, \xi_{i1}\xi_{i2}, \dots, \xi_{i,m-1}\xi_{im}) \tag{5.10}$$

$$\eta_i = \Omega\beta_i + \zeta_i, \quad \zeta \sim \mathcal{N}(0, \psi) \tag{5.11}$$

$$y_i = \eta_i \tag{5.12}$$

²Note that there is no intercept.

5.3.3 Bayesian Analysis

The usual way to estimate the parameters $\theta = \{\Omega, \Phi, \Psi, \Lambda_x, \Theta_\delta, \Lambda_y, \Theta_\varepsilon\}$ has been the classical frequentist approach. A popular method to compute an approximation of the posterior distribution over the parameters of SEM is maximum likelihood (ML). Under very mild conditions, this estimation methods give unbiased estimates. However, in several cases, such as small sample size and nonlinearity, this estimation method is often not optimal. Furthermore, in general, the product indicator method (Kenny and Judd, 1984) is used to analyze models with interaction terms of latent variables. However, psychometric research indicates several methodological problems when implementing interactions in latent variable models using traditional methods (Jöreskog and Yang, 1996).

Since methodological complexities arise when implementing a nonlinear latent variable model utilizing the frequentist approach (in combination with the product indicator method), Arminger and Muthén (1998) propose to use a Bayesian approach for model estimation. Recently, in a comparative study, Lee, Song and Poon (2004) show that the Bayesian approach is in general better than the product indicator approach. Applying Markov Chain Monte Carlo (MCMC) methods, such as the Gibbs sampler, have many advantages in the present context. Foremost, we do not have to rely on asymptotic inference. Basically, several studies indicate that sample size matters for the behavior of structural equation modeling estimators (Bearden, Sharma and Teel, 1982; Boomsma, 1985; Chou, Bentler and Satorra, 1991; Hoogland and Boomsma, 1998) and it is generally concluded that maximum likelihood is not robust for small sample sizes.³ Therefore, several scientists recommend the use of MCMC methods in the case of small sample size (Armingier and Muthén, 1998; Scheines, Hoiijtink and Boomsma, 1999; Lee, 1981). For example, Scheines et al. (1999) demonstrate that standard errors calculated from MCMC output are more reliable for small samples or when there are other sources of non-normality. A second advantage of a Bayesian analysis is that it offers the flexibility to incorporate prior managerial knowledge. For example, we can constrain the parameters to be positive or negative. Also, inequality restrictions can be implemented in the sampling procedure. These restrictions can be set on the parameter estimates, estimated standard errors and interval estimates (Scheines et al., 1999).

In Bayesian inference, in contrast to the frequentist inference, the parameters in θ are considered to be random. The Bayesian approach combines prior information about model parameters with information contained in the data to arrive at the posterior distribution. The posterior density of θ given the covariance matrix Σ is defined as (Scheines et al., 1999)

$$p(\theta|\Sigma) = \frac{p(\Sigma|\theta)p(\theta)}{\int p(\Sigma|\theta)p(\theta) d\theta} \quad (5.13)$$

³Note that the assumptions of multivariate normality and a correctly specified model is made. Frequently, the assumption of normality is not satisfied leading to (possibly) improper solutions.

where the denominator represents the marginal likelihood (a normalizing constant). The calculation of the marginal likelihood is however very challenging. Therefore, MCMC methods are generally used to generate draws from the joint posterior distribution

$$p(\theta|\Sigma) \propto p(\Sigma|\theta)p(\theta) \quad (5.14)$$

Gibbs Sampling

In a Bayesian approach, we need to analyze the posterior distribution. Posterior distributions can be approximated to arbitrary precision with the Gibbs sampler (Gelfand and Smith, 1990; Geman and Geman, 1984). First, this method is utilized to generate a sequence of random observations from the joint posterior distribution. Then, the solution is obtained by means of generated observations. The posterior distribution for the linear models is trivial and can be approximated with the Gibbs sampler. However, the posterior distribution for a nonlinear latent variable model is quite complex. Arminger and Muthén (1999) have shown that utilizing the Gibbs sampler in this case is rather complicated since no closed mathematical form of the distribution of the latent variables exists. A plausible solution is to use the Metropolis-Hastings algorithm (Hastings 1970; Metropolis et al. 1953)).

Prior Distributions

To derive the conditional distributions, we need to specify the prior distributions for the random parameters. As noted before, the random variable η , ξ , ε and ζ are multivariate normal with $\eta \sim N(0, \phi)$, $\xi \sim N(0, \Psi)$, $\varepsilon \sim N(0, \Theta_\varepsilon)$ and $\zeta \sim N(0, \Theta_\zeta)$. In this study we use conjugate prior distributions, which have been found to be flexible and convenient (Lindley and Smith, 1972). The conjugate prior for the covariance matrix Ψ is given in terms of the inverse Wishart distribution

$$\Psi \sim \mathcal{W}^{-1}(d_\Phi \Omega_\Phi, d_\Phi) \quad (5.15)$$

where $d\Omega$ is a precision matrix and d refers to degrees of freedom; for a detailed discussion of the Wishart distribution, see Anderson (1984). The conjugate covariance matrix Φ is given by

$$\Phi \sim \mathcal{W}^{-1}(d_\Phi \Omega_\Phi, d_\Phi) \quad (5.16)$$

The conjugate priors for the variances of the error term, Θ_ε and Θ_δ , follow inverse Gamma distributions

$$\Theta_\varepsilon \sim \mathcal{IG}(a_\varepsilon, b_\varepsilon) \quad (5.17)$$

$$\Theta_\delta \sim \mathcal{IG}(a_\delta, b_\delta) \quad (5.18)$$

5.3.4 Model Choice

Model choice is a fundamental activity in structural equation modeling. In order to assess the model performance, several types of model selection criteria have been proposed, such as the Bayes factor (Kass and Raftery 1995), Bayesian information criterion (Schwarz 1978), Gelfand and Ghosh criterion (Gelfand and Ghosh 1998) and the deviance information criterion (Spiegelhalter, Best, Carlin and van der Linde 2002). In a structural equation modeling context, only the Bayes factor has been explicitly investigated and recommended as the appropriate model choice procedure (Raftery 1993); the Bayes factor and Bayesian information criterion is also recommended and applied by Lee and colleagues (Lee and Song, 2001; Song and Lee, 2001; Song and Lee, 2002). However, the Bayes factor and the Bayesian information criterion have been seriously criticized as formal model comparison tools (see for example, Gelman and Rubin 1995; Spiegelhalter and Smith 1982; Zhu and Carlin 2000). On the other hand, both the deviance information criterion (DIC) and Gelfand and Ghosh's criterion (GGC) are very simple and research indicates good properties for these procedures. For example, Berg, Meyer and Yu (2004) demonstrate that DIC has strong discriminating power, even when the dimension of the parameter space is large. Concerning GGC, Wang and Ghosh (2004) show that this procedure performs well in suggesting the correct model. Since the DIC procedure is generally known, we refer to Spiegelhalter et al. (2002) for a detailed discussion on the features and implementation of this method. Concerning the GGC procedure we refer to chapter 4.

5.3.5 The Models

The model specification for the linear latent model can be expressed using the following equation (the regression constant is set to 0)

$$\eta = \alpha_1 \xi_1 + \alpha_2 \xi_2 + \alpha_3 \xi_3 + \alpha_4 \xi_4 + \alpha_5 \xi_5 + \alpha_6 \xi_6 + \zeta \quad (5.19)$$

where η refers to an endogenous construct, which is firm performance in this case. $\xi_1, \xi_2, \xi_3, \xi_4, \xi_5$ and ξ_6 are vectors of exogenous constructs and represent customer-driven, competitor-driven, supplier-driven, technology-monitoring, customer-relating and supplier-relating capabilities, respectively. The following proper priors are used for the structural model: $\alpha = (\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6)^T \sim \mathcal{N}(\bar{\alpha}, \Omega_\alpha)$ with $\bar{\alpha} = (1, 1, 1, 1, 1, 1)$ and $\Omega_\alpha^{-1} = \text{diag}(.01, .01, .01, .01, .01, .01)$; $\Phi \sim \mathcal{W}^{-1}(d_\Phi \Omega_\Phi, d_\Phi)$ where $\Omega_\Phi = \text{diag}(.01, .01, .01, .01, .01, .01)$ and $d_\Phi = 6$. For the measurement model, we have the following priors, $\lambda_{x,j} \sim \mathcal{N}(\bar{\lambda}_{x,j}, \Omega_{\lambda_{x,j}})$ with $\bar{\lambda}_{x,j} = 1.0$, and $\Omega_{\lambda_{x,j}}^{-1} = .01$, where j represents the nonfixed parameters; $\Theta_{\delta,jj} \sim \mathcal{IG}(a_{\delta,jj}, b_{\delta,jj})$ with $a_{\delta,jj} = -1/2$ and $b_{\delta,jj}^{-1}$ for $j = 1, \dots, 38$.

The nonlinear latent variable model can be written as

$$\begin{aligned} \eta = & \beta_0 + \beta_1\xi_1 + \beta_2\xi_2 + \beta_3\xi_3 + \beta_4\xi_4 + \beta_5\xi_5 + \beta_6\xi_6 \\ & + \beta_7(\xi_1\xi_5) + \beta_8(\xi_1\xi_6) + \beta_9(\xi_2\xi_5) + \beta_{10}(\xi_2\xi_6) \\ & + \beta_{11}(\xi_3\xi_5) + \beta_{12}(\xi_3\xi_6) + \beta_{13}(\xi_4\xi_5) + \beta_{14}(\xi_4\xi_6) + \zeta \end{aligned} \quad (5.20)$$

The priors for this model are the same as for the linear latent variable model.

5.4 Results

For the analyses described in this article, the Gibbs sampler is run. All computations are performed using WinBUGS, a freely available software for Bayesian inference Using Gibbs Sampling (Spiegelhalter, Thomas, Best and Lunn 2004). The convergence of the Gibbs sampler is monitored by the ‘estimated potential scale reduction’ (EPSR) value as described by Gelman and Rubin (1992).

5.4.1 Confirmatory Factor Analysis

Before estimating the propositions, we refine the strategic marketing capabilities construct to make it agree better with the observed data. In this purification stage, we eliminate the least aligned items and estimate the model. We use parameter convergence, model fit, the 95 percent coverage of the median, the average of the median, the unstandardized coefficients and standard deviations to refine the construct. In general, the model parameters converge in less than 18.000 iterations; the EPSR values are less than 1.2 in all cases. The Gibbs sampler is therefore run for 50.000 iterations. The first 20.000 iterations are the burn-in samples. Inferences are based on the last 30.000 iterations. The results are shown in table 5.1. To avoid clutter, only the posterior mean and standard deviations of the eta’s, lambda and precision over the 20.000 samples are given. For the eta’s, we also give the 95 percent coverage and the average of the median. In general, the unstandardized coefficients and standard deviations are considered satisfactory; the posterior mean of the parameters in practically all cases are at least twice as great as the posterior standard deviations and therefore considered significant.

5.4.2 The Linear Latent Variable Analysis Outcomes

Our framework posits direct main effects of strategic marketing capabilities on firm performance. Before discussing the model outcomes, we discuss model fit and convergence issues.

A fundamental notion in structural equation modeling is the assessment of fit. Scheines et al. (1999) propose to use a Bayesian counterpart of the classical tests for goodness of fit to judge the fit of a single Bayesian model to the observed data originally developed by Rubin (1984) (see for a detailed discussion, Gelman, Meng

Dimension							
	Subdimension		mean	sd	2.5%	median	97.5%
CUSTDC	cusdc_ig	eta	0.182	0.121	0.009	0.166	0.452
	cusdc_id	eta	0.240	0.083	0.073	0.243	0.397
	custdc_resp	eta	0.505	0.203	0.116	0.488	0.900
COMDC	comdc_ig	eta	0.413	0.086	0.245	0.414	0.578
	comdc_id	eta	0.392	0.082	0.231	0.392	0.552
	comdc_resp	eta	0.528	0.081	0.373	0.528	0.690
SUPPDC	suppdc_ig	eta	0.287	0.143	0.024	0.291	0.561
	suppdc_id	eta	0.286	0.148	0.020	0.293	0.557
	suppdc_resp	eta	0.202	0.119	0.013	0.197	0.445
TMC	tmc_ig	eta	0.566	0.087	0.380	0.570	0.727
	tmc_rd	eta	0.675	0.093	0.463	0.682	0.838
CRC	crc_is	eta	0.294	0.106	0.060	0.300	0.492
	crc_coop	eta	0.369	0.144	0.064	0.376	0.638
SRC	src_is	eta	0.401	0.113	0.148	0.410	0.602
	src_coop	eta	0.397	0.121	0.121	0.404	0.614
	Items		mean	sd		mean	sd
CUSTDC	custdc_ig	lambda	1.000		precision	0.624	0.121
	custdc_id	lambda	1.329	0.377	precision	0.374	0.200
	custdc_resp	lambda	1.000		precision	0.907	0.120
	custdc_id	lambda	2.074	0.295	precision	0.067	0.129
	custdc_resp	lambda	1.000		precision	0.340	0.181
COMDC	custdc_resp	lambda	0.691	0.175	precision	0.700	0.110
	comdc_ig	lambda	1.000		precision	0.219	0.055
	comdc_id	lambda	0.900	0.086	precision	0.358	0.061
	comdc_id	lambda	1.000		precision	0.334	0.064
	comdc_id	lambda	0.935	0.100	precision	0.375	0.063
SUPPDC	comdc_resp	lambda	1.000		precision	0.450	0.065
	comdc_resp	lambda	1.325	0.132	precision	0.029	0.050
	suppdc_ig	lambda	1.000		precision	0.348	0.077
	suppdc_id	lambda	1.03	0.130	precision	0.329	0.079
	suppdc_id	lambda	1.000		precision	0.458	0.094
TMC	suppdc_id	lambda	0.980	0.161	precision	0.529	0.101
	suppdc_resp	lambda	1.000		precision	0.499	0.084
	suppdc_resp	lambda	1.048	0.155	precision	0.506	0.093
	tmc_ig	lambda	1.000		precision	0.244	0.052
	tmc_ig	lambda	1.103	0.091	precision	0.073	0.053
CRC	tmc_re	lambda	1.000		precision	0.025	0.035
	tmc_re	lambda	0.866	0.057	precision	0.269	0.044
	crc_is	lambda	1.000		precision	0.599	0.085
	crc_is	lambda	1.242	0.159	precision	0.331	0.072
	crc_is	lambda	1.15	0.158	precision	0.427	0.076
SRC	crc_coop	lambda	1.000		precision	0.353	0.086
	crc_coop	lambda	0.921	0.129	precision	0.448	0.084
	src_is	lambda	1.000		precision	0.409	0.075
	src_is	lambda	1.032	0.132	precision	0.368	0.075
	src_coop	lambda	1.000		precision	0.441	0.076
	src_coop	lambda	1.333	0.157	precision	0.05	0.076

Note: ig is intelligence generation, id is intelligence dissemination, resp is responsiveness, re is research and development, is refers to information sharing, and coop is cooperation.

Table 5.1: Parameter Estimates

and Stern 1996). The proposed linear model relating strategic marketing capabilities to firm performance adequately represents the data since a check criterion, which compares a replicated mean error sum of squares with the observed one, of .49 is obtained.

In general, the model parameters converge in less than 12.500 iterations; the EPSR values are less than 1.2 in all cases. Figure 5.2 depicts the EPSR value for the regression coefficients. Therefore, the Gibbs sampler is run for 32.500 iterations. The first 12.500 iterations are the burn-in samples. Inferences are based on the last 20.000 iterations.

The results of the linear models are presented in table 5.2. With respect to the effect of customer-driven capabilities on firm performance, hypothesis 1a posits that the higher a firm's customer-driven capabilities, the higher the financial per-

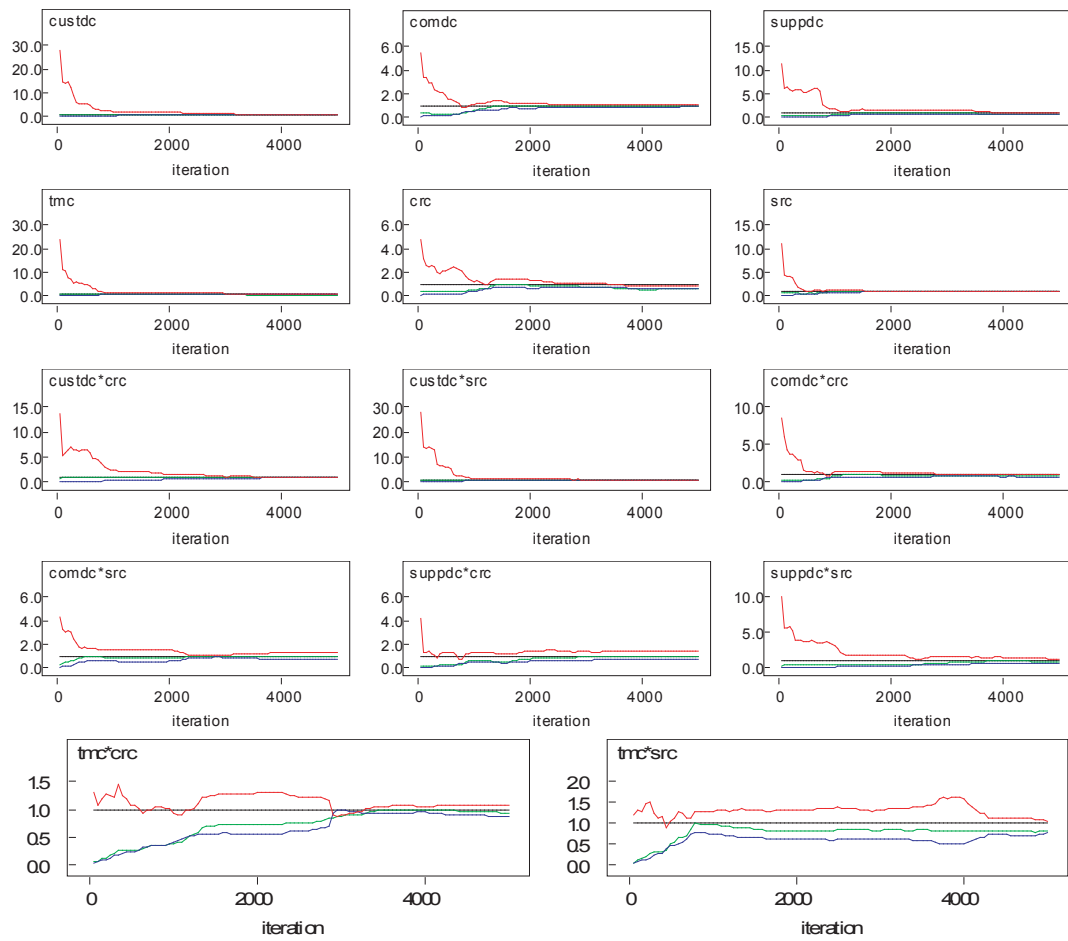


Figure 5.2: The EPSR value for the linear model

formance of the firm. This hypothesis is supported ($\beta = .29$, $sd = .076$). Consistent with hypothesis 1b, it is found that the degree of competitor-driven capabilities has a significant strong positive effect on firm performance ($\beta = .22$, $sd = .096$). Supplier-driven capabilities have a positive but slightly nonsignificant effect on firm performance ($\beta = .18$, $sd = .124$). Thus, hypothesis 1c receives no support. With respect to the effect of technology-monitoring capabilities on firm performance, hypothesis 1d posits that the higher a firm's technology-monitoring capabilities, the higher the financial performance of the firm. This hypothesis is partially supported ($\beta = .16$, $sd = .081$). Although a 95 percent coverage interval provides no support for this hypothesis, a 90 percent coverage interval did support the hypothesis. Hypothesis 1e proposes that customer-relating capabilities have a positive effect on firm performance. Support is found for this hypothesis ($\beta = .27$, $sd = .094$). Concerning hypothesis 1f, our analysis indicates a strong positive significant effect of supplier-relating capabilities on firm performance ($\beta = .51$, $sd = .118$). This result offers support for this hypothesis.

Independent Variable	mean	sd	2.5 %	median	97.5 %
Customer-Driven Capabilities	0.29	0.076	0.149	0.288	0.440
Competitor-Driven Capabilities	0.22	0.096	0.033	0.213	0.404
Supplier-Driven Capabilities	0.18	0.124	-0.037	0.166	0.471
Technology-Monitoring Capabilities	0.16	0.081	-0.016	0.156	0.309
Customer-Relating Capabilities	0.27	0.094	0.123	0.256	0.499
Supplier-Relating Capabilities	0.51	0.118	0.318	0.483	0.784

Table 5.2: Outcomes Linear Latent Variable Model

5.4.3 The Nonlinear Latent Variable Analysis Outcomes

Our second hypothesis suggests an interaction effect among the market-based capabilities on business performance. Concerning model fit, the check criterion for this model is also considered satisfactory; a value of .48 is obtained. By this standard, the model fits the data well. Furthermore, figure 5.3 suggests good convergence properties for the latent variable model parameters. The model parameters converge in less than 5000 iterations. As for the linear model, the Gibbs sampler is run for 32.500 iterations. The first 12.500 iterations are the burn-in samples. Inferences are based on the last 20.000 iterations.

Table 5.2 presents the results of the nonlinear latent variable analysis. This table shows several significant interactions, both positive and negative. Concerning hypothesis 2a, it is found that the interaction between customer-driven and customer-relating capabilities did not influence firm performance ($\beta = .02$, $sd = .121$). Thus, this hypothesis receives no support. Hypothesis 2b posits that the effect of customer-driven capabilities on firm performance is moderated by supplier-relating capabilities. The analysis indicates that seeking to possess high levels of both customer-driven and supplier-relating capabilities may have a negative effect on firm performance ($\beta = -.15$, $sd = .104$). However, the beta coefficient is slightly nonsignificant. Thus hypothesis 2b receives no support. Both hypothesis 2c and 2d indicate a contingent nature of the influence of competitor-driven capabilities on firm performance. Surprisingly, results show that the interaction between competitor-driven and customer-relating capabilities has a negative effect on firm performance ($\beta = -.26$, $sd = .142$), whereas the interaction between competitor-driven and supplier-driven capabilities has a positive impact on the financial performance of a firm ($\beta = .25$, $sd = .115$). Hypothesis 2e posits that the effect of supplier-driven capabilities on firm performance is moderated by the existence of customer-relating capabilities. This hypothesis is not supported ($\beta = -.08$, $sd = .149$). Although we hypothesize a synergistic effect between supplier-driven and supplier-relating capabilities, our analysis suggests the opposite ($\beta = -.20$, $sd = .093$). Hence, the effect of supplier-driven capabilities on firm performance tends to be moderated by the supplier-relating capabilities. Both hypothesis 2g and 2h indicate a contingent nature of the influence of technology-monitoring capabilities on firm performance. Both hypotheses are not supported.

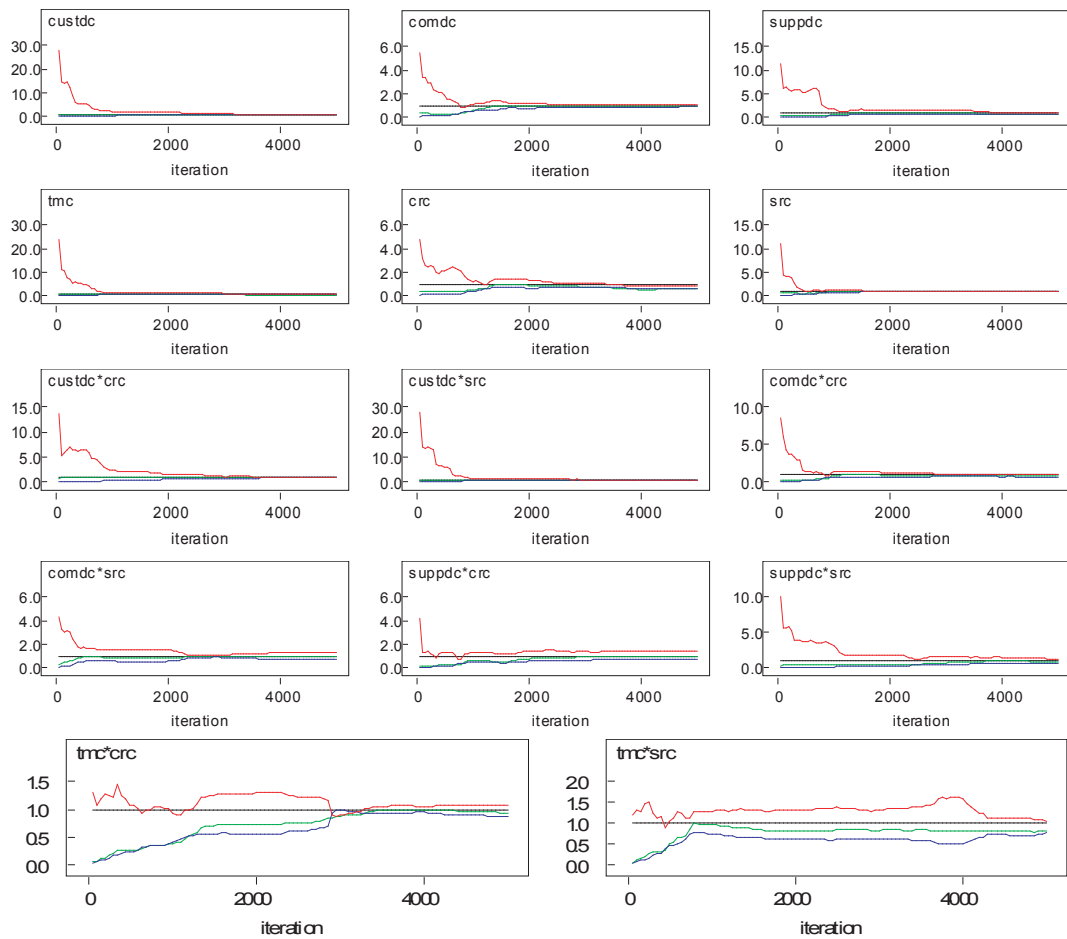


Figure 5.3: The EPSR value for the nonlinear model

5.4.4 Model Comparison

A fundamental task in structural equation modeling is model choice. We use two procedures to model choice, deviance information criterion (DIC) and Gelfand and Ghosh criterion (GGC). Concerning DIC, we encounter the problem of negative values for the effective number of parameters in a model. This even leads to a negative DIC. A simple explanation for why negative values appear in these cases is difficult to give. To formally compare the models, we only rely on GGC. A first impression is that GGC appears to work well; the MSPE shows quick and strong convergence in both cases. The MSPE value for both models is practically identical; a value of .354 (sd = .016) is obtained for the linear model and a value of .352 (sd = .016) for the nonlinear model.

Based on the outcomes reported in Table 5.3 and the meaningfulness of these results, we choose the nonlinear model as the most appropriate model. First, the Gelfand and Ghosh's criterion shows the best fit for this model, although the difference is fairly small. Second, a linear model is too simplistic and not very realistic

Independent Variable	mean	sd	2.5 %	median	97.5 %
Customer-Driven Capabilities (CDC)	0.26	0.097	0.085	0.257	0.475
Competitor-Driven Capabilities (COMDC)	0.23	0.106	-0.003	0.231	0.422
Supplier-Driven Capabilities (SDC)	0.16	0.137	-0.223	0.168	0.368
Technology-Monitoring Capabilities (TMC)	0.20	0.095	0.006	0.199	0.373
Customer-Relating Capabilities (CRC)	0.24	0.139	-0.090	0.272	0.455
Supplier-Relating Capabilities (SRC)	0.44	0.106	0.234	0.442	0.650
CDC x CRC	0.02	0.121	-0.231	0.036	0.248
CDC x SRC	-0.15	0.104	-0.357	-0.154	0.051
COMDC x CRC	-0.26	0.142	-0.609	-0.235	-0.045
COMDC x SRC	0.25	0.115	0.028	0.250	0.485
SDC x CRC	-0.08	0.149	-0.440	-0.073	0.169
SDC x SRC	-0.20	0.093	-0.396	-0.194	-0.014
TMC x CRC	-0.11	0.157	-0.388	-0.120	0.251
TMC x SRC	0.08	0.112	-0.177	0.081	0.293

Table 5.3: Outcomes NonLinear Latent Variable Model

Model	mean	sd	2.5 %	median	97.5 %
Linear Variable Model	0.354	0.016	0.324	0.354	0.385
NonLinear Variable Model	0.352	0.016	0.322	0.352	0.385

Table 5.4: Model Comparison

(Leeflang and Wittink, 2000; Leeflang et al., 2000). The previous let us to believe that the nonlinear model is more meaningful.

5.5 Discussion

Researchers in marketing management tend to adopt one of two approaches to examining competitive advantage: a focus on the market or a focus on relationships. In this study, we suggest that combining these approaches to examine competitive advantage will yield deeper insights. Building on prior research, we propose two models: (1) a main effects model, and (2) an interaction effects model. The results described in the previous section highlight some of the unique insights that emerge from this research approach.

Our main-effects model outcomes support the assertion that strategic marketing capabilities enhance financial value. The interaction effects model demonstrates the contingent nature of the influence of market-driven capabilities on firm performance. Surprisingly, results show that some combinations of strategic marketing capabilities have negative effects on the financial performance of the firm. For example, seeking high levels of supplier-driven and supplier-relating capabilities may erode firm performance. Findings also demonstrate that leveraging competitor-driven and customer-relating capabilities simultaneously to high levels may be harmful for a company, whereas the interaction between competitor-driven and supplier-relating

capabilities positively influences firm performance.

In this study, the DIC statistic appears to have some undesired properties. As mentioned before, a major problem of this statistic is the negative value generated for the number of effective parameters (P_D). We have seen this clearly in both the linear and nonlinear latent variable model. A simple explanation for why negative (P_D) appears in these cases is difficult to come with. Based on the previous, we believe that DIC is not very suitable in rather complex structural equation models. In saying this, we encourage research determining whether DIC can be applied appropriately in these classes of models.

In this study, Gelfand and Ghosh criterion (GGC) is applied to compare different models. GGC appears to work well; the MSPE shows quick and strong convergence in both cases. Despite this, we believe that further research examining more fully the performance of GGC suggesting the correct structural equation model is needed. Also, these studies may apply and compare other loss functions besides squared error loss.

Several researchers have argued that collaborative relationships are not appropriate for every market or customer. Our findings indeed indicate that building and maintaining strong relationships is a viable strategy, under certain conditions, for wholesalers to achieve competitive advantage. This is in line with Corsten and Kumar's (2005) outcomes. These researchers demonstrate that suppliers achieve greater economic performance and develop their capabilities in collaborative relationships. Our result also suggests that building strong relationship capabilities is only profitable under certain conditions. The analysis indicates that being driven by suppliers and simultaneously building strong relationships with the same suppliers is harmful. Possibly, this strategy requires extensive resources and the outcomes, because of power asymmetry and moral hazard etc., may not always be in favor of the firm.

This study suggests that a firm's ability to generate, disseminate and respond to relevant competitor's actions and strategies is a major component in generating financial performance in this industry. This is in line with previous research. Marketing researchers generally find that lacking competitor-driven capabilities reduce business performance (e.g., Clark and Montgomery, 1996). Therefore, Clark and Montgomery even suggest that "paranoia" may stimulate performance. However, developing competitor-driven capabilities is not in all situations the preferred strategy.

5.6 Management Implications

The strategic marketing capabilities construct represents a significant step forward in the evolution of the marketing concept. It provides an instrument for assessing the degree to which a firm is capable of sensing and relating to the market. In this article, we investigate the extent to which strategic marketing capabilities influence firm performance in a linear and nonlinear fashion. Our results may have implications for the business-to-business industry. Perhaps the main implication of

this study is that the development of both strong market-sensing and market-relating capabilities could be harmful for a company. This also provides some evidence why some powerful companies manage to perform bad. The management of marketing capabilities is an extremely complex task. The complexity of managing these capabilities leads us to believe that the development of these capabilities is a top management concern. This is also in line with former research suggesting the support of top management in developing strategic marketing capabilities (McNamara 1972; Webster 1988).

Our analysis also reveals the importance of market-relating capabilities in building strong firms. Based on this outcome, we believe that wholesale companies have to focus primarily on the management of relationships, especially with suppliers and other stakeholders. However, given the reported importance of market-driven capabilities, it is not recommended to neglect these capabilities. It is however highly advisable to promote and develop competitor-driven capabilities while maintaining high levels of supplier-relating capabilities.

5.7 Conclusion

Many companies consider investments in marketing capabilities as a means of increasing firm performance. This study indicates that this may not always be the case. This suggests that the management of marketing is a rather complex task that needs full involvement from (top) management.

Although this research provides insights into the relationship between strategic marketing capabilities and firm performance, further research investigating other relevant dependent variables, such as service quality, equity and trust, and research methodologies is necessary. The interplay between market-driven and market-relating capabilities in determining market performance is also a worthwhile and useful area for further research.