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Market-based capabilities, perceived quality and firm performance

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Chapter 4

The Strategic Marketing Capabilities Construct: An Integration of the Market-Driven and Relationship Marketing Perspectives

Abstract Researchers in marketing management 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). The authors suggest that combining these approaches to examine competitive advantage will yield better insights. Therefore, they synthesize these views by developing the ‘strategic marketing capabilities’ construct with the following dimensions: (1) customer-driven capabilities, (2) competitor-driven capabilities, (3) supplier-driven capabilities, (4) technology-monitoring capabilities, (5) customer-relating capabilities and (6) supplier-relating capabilities. This construct is tested with data from 137 electrotechnical wholesalers in the Netherlands utilizing a Bayesian approach to confirmatory factor analysis. The results indicate that the hypothesized strategic marketing capabilities model is a good representation of the variance-covariance matrix. Validation tests, applying a recently proposed information criterion called deviance information criterion and Gelfand and Ghosh’s criterion, using nested and nonnested competing models, are supportive for the proposed factor structure. The implications of these findings are discussed.

4.1 Introduction

Recently, marketing researchers begin to question the classical concept of market orientation (e.g., Achrol and Kotler 1999; Noble, Sinha and Kumar 2002; Parvatiyar and Sheth 2000; Vargo and Lusch 2004). It is suggested that this concept, that is developed in the late eighties, does not incorporate the complexity of today’s environment. Achrol and Kotler (1999) even argue that “The very nature of network organizations, the kinds of theories useful to its understanding, and the potential impact of the organization of consumption all suggest that a paradigm shift of marketing may not be far over the horizon” (p. 162).

Several scholars (e.g., Achrol and Kotler 1999; Day and Montgomery 1999; Hoekstra, Leeflang and Wittink 1999; Webster 1992) suggest that recent developments in both marketing theory and marketing practice make the integration of both the old marketing thoughts and relationship marketing necessary. The main reason behind this emerging stream of research is that the present conceptualizations

of market orientation (Kohli and Jaworski 1990; Narver and Slater 1990) hardly deals with the fundamental question: how do firms relate to their markets? Therefore, this stream of research suggests that the concept of market relatedness could be integrated with that of market orientation (Hunt and Lambe 2000; Vargo and Lusch 2004). In this context, Rust (2004) state that “Marketing is entering a new era, and mainstream marketing in the new era will closely resemble the business-to-business/service/relationship marketing of today” (p. 24). Some even suggest that relating to the market is the core of marketing (Grönroos 2000; Gummesson 2004). For example, Webster (1992) begins his thesis by stating that “A new conception of marketing will focus on managing strategic partnerships and positioning the firm between vendors and customers in the value chain with the aim of delivering superior value to customers. Customer relationships will be seen as the key strategic resource of the business (p. 1)”. Others prefer a less narrow general model of marketing. For example, Sheth and Parvatiyar (2000) suggest that “an alternative paradigm of marketing is needed, a paradigm that can account for the continuous nature of relationships among marketing actors” (p. 140). To address these issues, the authors draw on the market orientation and relationship marketing literature to further develop and refine the theory of market orientation.

In this study, we develop an integrated construct of market focus, which we call strategic marketing capabilities, by incorporating both market orientation (or market-driven capabilities) and relationship marketing (or market-relating capabilities) into one construct.¹ The idea of incorporating the management and marketing of market relationships into the marketing concept is not new. Day and Wensley (1983) and Lusch and Laczniak (1987) already suggest ‘market relationships’ as being part of the marketing concept. However, the empirical development of an integrated theory of market orientation is lacking. The emerging literature is largely conceptual and empirical research is still scarce. With this research, we try to fill this gap by drawing on and integrating different theoretical perspectives, empirical research and marketing practice to develop a concept of strategic marketing capabilities. This hierarchical construct represents the integration of market-driven capabilities and market-relating capabilities, and contains the following second-order factors: (1) customer-driven capabilities, (2) competitor-driven capabilities, (3) supplier-driven capabilities, (4) technology-monitoring capabilities, (5) customer-relating capabilities and (6) supplier-relating capabilities. Building on the classical concept of market orientation (Kohli and Jaworski 1990) and relationship marketing (e.g., Buvik and John 2000) we propose subdimensions (first-order factors) for the previously mentioned dimensions of strategic marketing capabilities. Furthermore, we include several competing models for comparison. Since our sample

¹There exist, in general, two views on today's marketing paradigm: (1) the American school, and (2) the Nordic school. The American school (among others Kohli and Jaworski 1990; Narver and Slater 1990) views market orientation as the implementation of the marketing concept, which holds the current marketing paradigm. On the other side, researchers such as Grönroos (1994, 2000) and Gummesson (1998) see relationship marketing as central to marketing. In this study, we argue that these views are complementary in nature and develop a model that incorporates these two perspectives.

size is rather limited and the models are not nested in all cases a Bayesian approach is developed to analyze the models. Also, we apply a recent statistic, called deviance information criterion, to compare both the nested and nonnested ((non)hierarchical) factor models. Another contribution of this study is the use of Gelfand and Ghosh's criterion (GGC) in comparing and choosing the best fitted model.

This chapter is organized as follows. In the next section, we discuss the concept of market orientation and introduce an integrated model we refer to as the strategic marketing capabilities construct. After that, methodological issues are described in detail. Finally, we test our construct, using data generated from customers of electrotechnical wholesalers in the Netherlands and discuss the outcomes.

4.2 Market Orientation

As already mentioned, there is some debate in the marketing literature concerning the domain of market orientation. The following views can be distinguished: market orientation as (1) activities (Kohli and Jaworski 1990), (2) a culture (Narver and Slater 1990), and (3) capabilities (Day 1994; Hooley, Broderick and Möller 1998). Next, we review the first two views, which represent the classical concept of market orientation. Then we outline the third view by discussing some models incorporating both the classical concept of market orientation and relationship marketing. This provides a rationale for our proposed model.

4.2.1 Classical Market Orientation

Several concepts of market orientation have appeared in the literature (e.g., Deshpandé et al. 1993; Kohli and Jaworski 1990; Narver and Slater 1990; Pelham and Wilson 1996; Reukert 1992). These concepts fall into two streams: (1) market orientation as a set of activities, and (2) market orientation as an organizational culture.

Market orientation as a set of activities

Market orientation as a set of activities refers to the firm's ability to generate market intelligence pertaining to current and future customer needs, dissemination of the intelligence across departments, and organizationwide responsiveness to it (Kohli and Jaworski 1990, p. 6). Another definition is that of Deshpandé and Farley (1998). They define market orientation as "the set of cross-functional processes and activities directed at creating and satisfying customers through continuous needs-assessment" (p. 213). A related view of market orientation is that of Reukert (1992). He defines market orientation as "the degree to which the business unit obtains and uses information from customers, develops a strategy which will meet customer needs, and implements that strategy by being responsive to customer's needs and wants" (p. 228). This perspective suggests a market orientation as a firm's capability in satisfying customer's needs and wants.

Market orientation as an organizational culture

Market orientation as a business culture is proposed by Narver and Slater (1990). They define market orientation as “the organizational culture that most effectively and efficiently creates the necessary behaviors for the creation of superior value for buyers and, thus, continuous superior performance for the business” (p. 21). They infer three behavioral components of market orientation: customer orientation, competitor orientation and interfunctional coordination. Like the previous one, this view has also gained broad acceptance in the marketing literature.

Comments on the classical concept of market orientation

The work of Kohli and Jaworski (1990) and Narver and Slater (1990) is seen as very fundamental to marketing. However, marketing researchers are questioning the comprehensiveness of present conceptualizations of market orientation (e.g., Noble, Sinha and Kumar 2002; Sheth and Parvatiyar 2000; Vargo and Lusch 2004). As noted before, present conceptualizations of market orientation are mainly criticized because they do not incorporate the extent to which a company is able to relate to the market. An emergent stream of research argues that building and maintaining relationships, besides information generation, dissemination and responsiveness, is an essential marketing capability that enables a firm to produce an offering well tailored to a market segment’s specific tastes and preferences (e.g., Grönroos 2000; Gummesson 2004; Vargo and Lusch 2004; Webster 1992). In this respect, Hunt and Lambe (2000) argue that “A key orientation that is missing in the present conceptualization of MO [market orientation] is a firm’s partnering orientation” (p. 28). Furthermore, the approach used by Narver and Slater (1990), despite their strong arguments, is actually ambiguous. First, the definition of ‘culture’ gives a lot of problems; different definitions of organizational culture have been suggested in the literature (e.g. Barney 1986; Denison and Mishra 1995; Deshpandé and Webster 1989; Hofstede, Neuijen, Ohayv and Sanders 1990). Denison and Mishra (1995) argue that limited consensus exists regarding a general theory of organizational culture. Therefore, Kennedy, Goolsby and Arnould (2003) suggest that the cultural approach of market orientation is difficult to investigate. Second, Homburg and Pflessner (2000, p. 449) suggest that the cultural perspective has had a stronger impact on the definition than on the conceptualization and the development of measures of market orientation. This is the reason why Deshpandé and Farley (1998) conclude that market orientation is not a culture, but more “a set of activities”. Cadogan et al. (2001, p. 263) state that “although terminology may differ, the consensus appears to be that a market orientation consists of activities associated with the gathering and dissemination of market intelligence and the appropriate analysis and response to that intelligence.”

4.2.2 Integrative View of Market Orientation

Recently, marketing scholars have recognized the shortcomings of the present conceptualizations of marketing orientation and proposed alternative conceptualizations; this by combining market orientation and relationship marketing into an extended concept of marketing (see for example, Day 1994; Hooley et al. 1998; Hooley et al. 1999; Hoekstra, Leeflang and Wittink 1999; Srivastava, Shervani and Fahey 1998, 1999; Vagro and Lusch 2004). Cravens (1998), for example, sums building and developing relationships with customers and channel members as a characteristic of market-driven strategies. Relationship marketing refers to the development, enhancement and when necessary termination of relationships with customers (and other parties), so that the objectives regarding economic and other variables of all parties are met (Grönroos 2000, p. 235). In this study, we deal with this emerging stream of research, which we refer to as an ‘integrative view of market orientation’. In this extended view of market orientation, the classical work of Day (1994) and Lusch and Lucznik (1987) represents the core. Although these marketing researchers start from different perspectives, they both integrate market drivenness and relatedness in developing their concept of marketing.²

Lusch and Lucznik (1987), building on the work of Pfeffer and Salancik (1978), Anderson (1982), Day and Wensley (1983) and Zeithaml and Zeithaml (1984), develop (as they call it) an extended marketing concept by integrating two constructs: (1) the marketing concept, and (2) the stakeholder concept. The marketing concept represents the classical model and the implementation of this concept is referred to as “market orientation.” The stakeholder concept refers to the management and development of relationships with the organization’s multiple stakeholders. Although they call it the ‘stakeholder concept,’ this dimension is strongly related to building and maintaining relationships (especially when considering their definition and measurement). Factor analytic methods indicate that these two concepts (market orientation and relationship orientation) indeed are representative of a single underlying philosophical business orientation. Their study suggests that integrating and investigating an integrated model of the marketing concept may lead to a better understanding of the implementation of this (marketing) concept.

Day (1994) takes a different perspective when developing his view of market orientation. Day argues that market-driven organizations have superior market-sensing, customer-linking and channel-bonding capabilities. Furthermore, he classifies these marketing capabilities into: (1) market-sensing capabilities, (2) customer-linking capabilities, (3) channel-bonding capabilities, and (4) technology-monitoring capabilities. After his novel work, other marketing researchers attempt to refine this concept and relate it to financial performance (e.g., Hooley et al. 1998; Srivastava et al. 1998). For example, Hooley et al.’s (1998) model of strategic marketing capabilities, which incorporates market and relationship dimensions, is closely related to Day’s marketing capabilities. Basically, this stream, although highly conceptual,

²Additionally, we could also report the strategic orientation perspective. Since we believe that the strategic orientation direction largely build on Day’s (1994) seminal work, we refer the interested reader to Gatignon and Xuereb’s (1997) article.

further refines Day's (1994) concept of strategic marketing capabilities and explicitly defend its relevance in developing market-based advantage.

In summary, this stream of research suggests that market-driven organizations emphasize and develop both market-driven and market-relating capabilities. Next, we introduce a model we call the strategic marketing capabilities construct, which encompasses both market-driven and market-relating capabilities.

4.2.3 An Integrated Model: Strategic Marketing Capabilities

We define strategic marketing capabilities as the firm's capability to sense and relate to the market. Concretely, firms with strong strategic marketing capabilities (1) acquire, develop and use market information to serve their market and (2) perform key customer and channel connecting processes. In developing our multilevel multidimensional strategic marketing capabilities construct, we largely build on Day's (1994) perspective. The reasons are: (1) Kohli and Jaworski's (1990) and Hooley et al.'s (1998) concepts are partially integrated in the approach of Day, (2) unlike Kohli and Jaworski's (1990) concept, it deals explicitly with relationship marketing aspects, and (3) there is a growing consensus that a market orientation is a capability (e.g., Day 1994; Grewal and Tansuhaj 2001; Hunt and Morgan 1995).

Figure 4.1 shows the hierarchical structure of our proposed strategic marketing capabilities construct. As can be seen, the construct includes the following six dimensions: (1) customer-driven capabilities, (2) competitor-driven capabilities, (3) supplier-driven capabilities, (4) technology-monitoring capabilities, (5) customer-relating capabilities and (6) supplier-relating capabilities. Furthermore, all subdimensions have two or three indicators. Using Day's (1994) classification, the first four components are a part of market-driven capabilities and customer-relating and supplier-relating capabilities are a part of market-relating capabilities.

Market-Driven Capabilities

Market-Driven Capabilities refer to "how well the organization is equipped to continuously sense changes in its market and to anticipate the responses to marketing actions" (Day, 1994, p. 49). Generally, the marketing literature puts a strong emphasis on customers and competitors (Day, 1994; Kohli and Jaworski, 1990; Narver and Slater, 1990). This stream of research splits market-driven capabilities into: (1) customer-driven capabilities, (2) competitor-driven capabilities. Growing numbers of studies, however, indicate that other stakeholders, such as suppliers, especially in a business-to-business context, are also important (e.g., Day and Montgomery, 1999; Greenley and Foxall, 1998; Langerak, 2001; Matsuno and Mentzer, 2000; Slater and Narver, 1995; Wind and Mahajan, 1997). Following these researchers, we believe that supplier-driven capabilities are part of a market-driven capabilities concept. Day (1994) has introduced and recently Srinivasan, Lilien and Rangaswamy (2002) have operationalized the technology-monitoring capabilities construct. In line with Day (1994), we believe that this marketing capability is essential for market-driven organizations. Also, the importance of this variable is also emphasized in the market

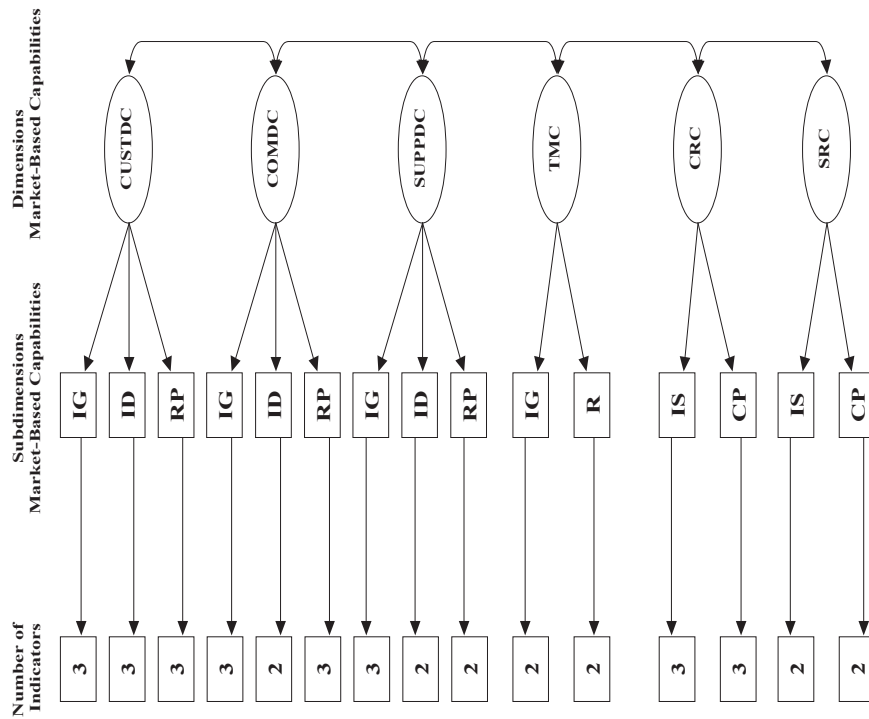


Figure 4.1: Proposed Factor Structure for the Strategic Marketing Construct. CUSTDC is customer-driven capabilities, COMDC is competitor-driven capabilities, SUPPDC is supplier-driven capabilities, TMC is technology-monitoring capabilities, CRC is customer-relating capabilities, SRC is supplier-relating capabilities, IG is intelligence generation, ID is intelligence dissemination, RP is responsiveness, R is research and development, IS information sharing and CP is cooperative collaboration.

orientation literature (e.g., Gatignon and Xuereb, 1997; Jaworski and Kohli, 1993). The benefit of high technology-monitoring capabilities is the ability to uncover unmet needs within existing or new market segments. Further, Srinivasan et al. (2002) have established the distinctiveness of the technology monitoring capability model from related constructs, such as organizational innovativeness, technological orientation and market orientation.

In summary, market-driven capabilities have the following dimensions: (a) customer-driven capabilities, (b) competitor-driven capabilities, (c) supplier-driven capabilities, and (d) technology-monitoring capabilities. The first three dimensions reveal the firm's capabilities to generate intelligence, disseminate this intelligence and implement a response based on the acquired market information (i.e., the subdimensions). The fourth dimension incorporates two subdimensions: (1) intelligence generation, and (2) research and development.

Market-Relating Capabilities

‘Getting close to the customer’ is a key ingredient in an organization’s attempt to provide quality and value for the customer (e.g. Kohli and Jaworski 1990; Narver and Slater 1990). Gruen et al. (2000) argue that a complementary but often overlooked task involves “getting the customer closer to the organization” (p. 39). Getting the customer closer, or market-relating, can be done by distributing relevant information to the customer about the organization’s processes, personnel, and so forth (Buvik and John 2000; Day 1994; Gavirneni, Kapuscinski and Tayur 1999; Macneil 1980; Rosenzweig, Roth and Dean 2003) and by collaborative cooperation with the customer (Day, 1994; Håkansson 1982; Rozenzweig et al. 2003). Kelley and Thibaut (1978), for example, suggest that information sharing stimulates exchange and leads to better understanding of the outcomes of mutual behaviors (see also for example, Macneil 1980; Morgan and Hunt 1994; Williamson 1985). Concerning collaborative cooperation, both the political economy model (Stern and Reve 1980) and the Nordic interaction framework (Håkansson 1982) suggest a key role for cooperation in relational exchange. Hence, these two dimensions of market-relating capabilities are generally accepted as relevant relationship marketing dimensions.

Day (1994) proposes a model that incorporates the potential of relationships with suppliers and other channel members. Other researchers also emphasize the relevance of relating to both customers and suppliers or channel members (e.g., Butaney and Wortzel 1988; Day 2000; Day and Montgomery 1999; Langerak 2001; Sigauw, Simpson and Baker 1998). Therefore, we distinguish two dimensions of market-relating capabilities: (1) customer-relating capabilities, and (2) supplier-relating capabilities.

4.2.4 Competing Models

To examine the degree to which our proposed factor structure (six second-order and fifteen first-order factors) is a better representation of the data or covariance matrix than other (possible) models, we compare our model to both several competing models (CM). Our proposition is that the factor structure previously discussed for our strategic marketing capabilities construct outperforms the competing models. We investigate the following theoretically plausible competing models (CM) of strategic marketing capabilities:

CM I: one-factor model. This model suggests that the covariation among indicators can be accounted for by a single factor. Hence, this indicates that all indicators belong to one construct.

CM II: two-factor model. In this model, we propose that the covariation among the items can be accounted for by a two-factor model; the first factor consisting of market-driven capabilities indicators and the second factor representing market-relating capabilities indicators.

CM III: six first-order factors. Though we conceptualize our model as consisting of six second-order factors, with fifteen first-order factors, one can argue that a six first-order factor model, by referring to market orientation studies, may fit the

covariation matrix better. This model investigates this proposition.

CM IV: fifteen first-order factor model. Our proposed model consists of fifteen first-order and several second-order factors. With calculating this competing model, we get a first impression about the appropriateness of the factor structure proposed for the strategic marketing capabilities model. Since our original proposed model incorporates fifteen first-order factors, we anticipate a better fit for this model compared with the previous competing models.

CM V: six first-order factors, one second-order factor. This model suggests that the covariation among indicators can be accounted for by a single second-order factor and six first-order factors.

CM VI: six first-order factors, two second-order factors. In this model, we propose that the covariation among the items can be accounted for by a two second-factor model, the first second-order factor consists the dimensions customer-driven capabilities, competitor-driven capabilities, supplier-driven capabilities and technology-monitoring capabilities. The second second-order factor has two first-order factors, customer-relating capabilities and supplier-relating capabilities.

CM VII: fifteen first-order factors, one second-order factor. This model suggests that the covariation among indicators can be accounted for by a single second-order factor and fifteen first-order factors.

CM VIII: fifteen first-order factors, two second-order factors. This model's factor structure differs from our proposed one in that it has two second-order factors. The first second-order factor, market-driven capabilities, incorporates the dimensions customer-driven capabilities, competitor-driven capabilities, supplier-driven capabilities and technology-monitoring capabilities while the second higher-order factor, market-relating capabilities, consists of the components customer-relating capabilities and supplier-relating capabilities. Since this model is close to our proposed factor structure, we anticipate a better fit for this model compared to the other competing models. When this is true it provides additional support for our proposed factor structure.

4.3 Method

4.3.1 Measurement

This section explains the operationalization of the construct dimensions. Measures of the constructs we examine are available in the literature. All constructs under study are modified to suit the wholesale environment (Coughlan, Anderson, Stern and El-Ansary 2001; Roosenbloom 1999) and are measured on a seven-point Likert scale (see Appendix C).

The Market-Driven Capabilities Components

Several authors have examined Jaworski and Kohli's (1993) scale (Bhuian, 1998; Cadogan, Diamantopoulos and de Mortanges, 1999; Deshpandé and Farley, 1998; Matsuno and Mentzer, 2000; Oczkowski and Farrell, 1998). The results in-

dicating low reliability for the three first-order factor model. As a solution, several studies have integrated and modified Kohli and Jaworski's (1990) and Narver and Slater's (1990) conceptualization to develop a stronger measure (Deshpandé and Farley, 1998; Langerak, 2001; Pelham, 2000). In this study, we follow this perspective. We integrate and modify Kohli and Jaworski's (1990) and Narver and Slater's (1990) conceptualizations and measure market-driven capabilities as the firm's skills to (1) gather and (2) disseminate market information from customers, competitors and suppliers, and (3) implement a response based on this (market) information. In measuring technology monitoring capabilities, we partially use the 'technology-sensing capabilities' scale, validated by Srinivasan et al. (2002). The technology-monitoring capabilities scale has two first-order factors: (1) intelligence generation, and (2) research and development.

The Market-Relating Capabilities Components

For the customer-relating and supplier-relating capabilities scales, measures are gathered from different sources (Doney and Cannon 1997; Lusch and Brown 1996; Rozensweig et al. 2003). These two scales have the following first-order factors: (1) collaborative information sharing, and (2) collaborative cooperation. Indicators for the information sharing scales are derived from Buvik and John's (2000), Doney and Cannon's (1997) and Lusch and Brown's (1996) studies. The items belonging to the second subdimension, collaborative cooperation, are derived from Buvik and John's (2000) and Rosenzweig et al.'s (2003) studies.

4.4 Analytical Methods

Confirmatory factor analysis is used to estimate a model composed of fifteen first-order (the subdimensions) and six second-order, latent factors (the dimensions) (figure 4.1). The appropriate way to analyze this measurement model is to apply hierarchical confirmatory factor analysis. To further examine the strength of this model, we compare it to eight competing models. Several complexities, such as the small sample size and number of parameters to be estimated, led us to utilize a Bayesian approach to confirmatory factor analysis.

4.4.1 Factor Analysis

Standard confirmatory factor analysis

Following LISREL notation, the first-order linear confirmatory factor analysis model can be presented as (Jöreskog and Sörbom 1996)

$$x = \Lambda\xi + \delta \tag{4.1}$$

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 and measure specificity. It is assumed that the x 's are independent, ξ is independently distributed as $\mathcal{N}[0, \Phi]$, δ is independently distributed as $\mathcal{N}[0, \Psi_\delta]$, where Ψ_δ is diagonal and δ and ξ are uncorrelated.

Hierarchical confirmatory factor analysis

In this study, we develop a hierarchical model of strategic marketing capabilities. Previous research demonstrates the strength of this factor structure (see for example, Matsuno, Mentzer and Özsomer 2002). To analyze this hierarchical model, we apply hierarchical confirmatory factor analysis. This hierarchical factor structure accounts for the lower-order factors. The lower-order (first-order) may be expressed as

$$y = \Lambda\eta + \varepsilon \quad (4.2)$$

where y represents the vector of observed variables, Λ is a factor loadings matrix, η refers to a vector of latent variables and ε is a vector of measurement error. The higher order (second-order) structure may be presented as

$$\eta = \Gamma\xi + \zeta \quad (4.3)$$

where Γ is a $m \times n$ matrix, where m represents the number of endogenous (η s) factors and n represents the number of exogenous (ξ s) factors, and ζ refers to measurement error. The observed variance-covariance matrix can be presented as

$$\Sigma = \Gamma(\Lambda\Phi\Lambda' + \Psi)\Gamma + \Theta\epsilon \quad (4.4)$$

where, $\Theta\epsilon$ is a diagonal matrix of second-order residual variances, Ψ is a diagonal covariance matrix (with elements ψ). This equation can be reduced to a first-order factor model by forcing Γ to be an identity matrix and Ψ to be a null matrix.

4.4.2 Bayesian Analysis

Since we encountered several problems when implementing the proposed factor structure for our strategic marketing capabilities model utilizing the frequentist approach, such as unstable estimates due to sample size and Heywood cases, we therefore apply a Bayesian perspective for model estimation. The advantage of applying the Bayesian approach in the case of large numbers of parameters relative

to the sample size is frequently reported in the literature (e.g., Efron and Morris, 1971; 1972). Therefore, several researchers prefer the Bayesian approach in (complex) confirmatory factor analysis (Arminger and Mutén 1998; Lee and Song 2004; Scheines, Hoijsink and Boomsma 1999; Stern and Jeon 2004).

Let θ be the parameters and Σ the observed covariance matrix. In Bayesian inference, in contrast to the frequentist approach, the parameters in θ are considered to be random. The Bayesian framework allows the incorporation of prior information by specifying a prior distribution for the model parameters. The posterior density of θ given the sample covariance matrix Σ is defined as (Gelman, Carlin, Stern and Rubin, 2004; Lee, 1981)

$$\pi(\theta|\Sigma) = \frac{\pi(\Sigma|\theta)\pi(\theta)}{\int \pi(\Sigma|\theta)\pi(\theta)d\theta} \propto \pi(\Sigma|\theta)\pi(\theta) \quad (4.5)$$

where π denotes a probability density function and \propto stands for ‘is proportional to.’ In a Bayesian approach, we need to analyze the posterior distribution. Posterior distributions over the parameters of a confirmatory factor analysis 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.

To derive the conditional distributions, we need to specify the prior distributions for the random parameters. In this study we use conjugate prior distributions, which have been found to be flexible and convenient (Lindley and Smith 1972). The conjugate priors for the Λ ’s and Γ ’s are given in terms of the normal distribution. The precision matrix follows a Gamma distribution. The prior for the covariance matrix is given in terms of the inverse Wishart distribution. For a detailed discussion of different forms of prior distribution and the iteration scheme of the Gibbs sampler we refer to Lee (1981) and Song and Lee (2001, 2002).

Applying Markov Chain Monte Carlo (MCMC) methods, such as the Gibbs sampler, has 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 confirmatory factor analysis 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. Therefore, several scientists recommend the use of MCMC methods in the case of small sample size (Arminger and Mutén 1998; Scheines, Hoijsink and Boomsma 1999; Lee and Song 2004). For example, Scheines et al. (1999) argue 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 the Bayesian approach is that it offers the flexibility to incorporate prior 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).

4.4.3 Model Choice

Bayesian methods have been efficient in estimating parameters of (complex) factor models. A fundamental task in confirmatory factor analysis is model choice. Several criteria have been proposed in the literature for model comparison in the field of structural equation modeling. One can use posterior predictive p-values (Meng, 1994; Rubin, 1984) to evaluate the likelihood ratio goodness-of-fit statistic. However, this value only indicates the discrepancy between the posited model and the observed data. Therefore, Song and Lee (2002) among others argue that the posterior predictive p-value may not be suitable to compare different models. Raftery (1993) outlines a Bayesian approach to model selection for structural equation models. Both Bayes factors (Kass and Raftery 1995) and Bayesian information criterion (Schwarz, 1978) are also recommended and applied by Lee and colleagues (Lee and Song 2001; Song and Lee 2001, 2002). However, the Bayes factor and its approximations have been seriously criticized as formal model comparison tools (see for example, Gelman and Rubin 1995; Spiegelhalter and Smith 1982; Zhu and Carlin 2000). A major drawback of the Bayes factor is that it is not well defined in the case of improper priors. Gelman and Rubin (1995) even comment that in the models with improper prior distributions, which are generally used in model estimation, the Bayes factor is undefined. Even the case where priors are highly informative it can become a computationally intensive task to calculate Bayes factors when the dimension of the parameter space is large.

In our case, the number of unknown parameters is large and we do not possess complete information about the parameters, which makes the use of the Bayes factor and its approximations very difficult. A recent simple criterion for model selection, which is robust to the type (and change) of prior distributions, is the deviance information criterion (Spiegelhalter, Best, Carlin and van der Linde 2002). Recently, Berg, Meyer and Yu (2004) demonstrate that this criterion has strong discriminating power, even when the dimension of the parameter space is large. Although this criterion seems to have good properties, it can also give a negative value for the effective number of parameters in a model. Another statistic to extract the best model is the so-called Gelfand and Ghosh's (1998) criterion (GGC). In a simulation study, Wang and Ghosh (2004) show that GGC performs well in suggesting the correct model. In short, we follow Kuha's (2004) reasoning that useful information for model selection can be obtained from several criteria and apply both DIC and GGC.

Deviance Information Criterion

Recently, Spiegelhalter et al. (2002) propose a relatively simple and pragmatic method for model assessment and comparison. Following Dempster's (1997) perspective for model choice in the Bayesian framework, these scientists develop a procedure based on the posterior distribution of the log-likelihood. An advantage of this procedure, as outlined by Zhu and Carlin (2000) is that it can be calculated for each model considered without analytical adaptation, complicated loss functions or

any matrix inversion. Using an information theoretical argument, Spiegelhalter et al. (2002) derive a measure P_D for the effective number of parameters in a model as the difference between the posterior mean of the deviance ($\bar{\theta}$) and the deviance at the posterior mean of the parameters of interest

$$P_D = \overline{D(\theta)} - D(\bar{\theta}) \quad (4.6)$$

where $D(\theta)$ indicate a generalization of the Akaike information criterion (AIC) based on the posterior distribution of the deviance statistic

$$D(\theta) = -2\text{Log} \{p(\Sigma|\theta)\} + 2\text{Log} \{f(\Sigma)\} \quad (4.7)$$

where $p(\Sigma|\theta)$ is the likelihood function for the observed covariance matrix Σ given the parameter vector θ , and $f(\Sigma)$ is a standardizing function of the data. Rewriting equation (4.6) results in a classical ‘plug-in’ measure of fit plus a measure of complexity

$$\overline{D(\theta)} = D(\bar{\theta}) + P_D \quad (4.8)$$

Finally, the deviance information criterion (DIC) may be expressed as³

$$DIC = D(\bar{\theta}) + 2P_D \quad (4.9)$$

$$DIC = \bar{D} + P_D \quad (4.10)$$

where the fit of a model is summarized by the posterior expectation

$$\bar{D} = E_{\theta|\Sigma}[D(\theta)] \quad (4.11)$$

and the complexity of a model is captured by the statistic P_D . Smaller values of DIC indicate a better fitting model. See Spiegelhalter et al. (2002) for a more elaborate discussion on the features and implementation of this method.

Gelfand and Ghosh’s Criteria

Gelfand and Ghosh (1998) propose a decision-theoretic model selection criterion based on the posterior predictive loss approach. The criterion developed by Gelfand and Ghosh (1998) (GGC) derives its strength from its simplicity. Besides

³Note that in the absence of any prior, DIC equals the well-known AIC.

its simplicity, the GGC has some other attractive properties. For example, it can be used to compare different nested and nonnested models. Also, it has an appealing interpretation as the sum of predictive variances and goodness-of-fit terms. Next, we briefly discuss this criterion (for a detailed discussion, see Gelfand and Ghosh 1998; for a simple discussion of the GGC statistic, see Ghosh and Norris (2005)).

Define Σ as the observed covariance matrix and Σ_{pred} as the predicted covariance matrix generated from the following posterior predictive distribution

$$\pi(\Sigma_{pred}|\Sigma) = \int \pi(\Sigma_{pred}|\theta)\pi(\theta|\Sigma)d\theta \quad (4.12)$$

where $\pi(\Sigma_{pred}|\theta)$ denotes the likelihood function evaluated at Σ_{pred} , and $\pi(\theta|\Sigma)$ is the posterior distribution of parameter θ given the observed covariance matrix. The next step is to define a loss function that measures the discrepancy between the observed covariance matrix and the predicted covariance matrix. An often used loss function (see also, Ghosh and Norris 2005) is the mean square predicted error (MSPE), which may be expressed as

$$\frac{1}{n} \sum_{i=1}^n (\Sigma_{pred} - \Sigma)^2 \quad (4.13)$$

Using this statistic as the loss function, the GGC is defined as $GGC = E(\text{MSPE}|\Sigma)$.

4.5 Findings

For the analyses described in this article, the Gibbs sampler is run. All computations are performed using WinBUGS, freely available software for Bayesian inference Using Gibbs Sampling (Spiegelhalter, Thomas, Best and Lunn 2004). For the hierarchical model, we truncate the eta's, the parameters that relate the second-order factors to their corresponding lower-order factors, above zero.

Since we use the Gibbs sampler, careful monitoring of burn-in and convergence is required. The convergence of the Gibbs sampler is monitored by the 'estimated potential scale reduction' (EPSR) value as described by Gelman and Rubin (1992). In general, the model parameters converge in less than 20.000 iterations; the EPSR values are less than 1.2 in all cases. Furthermore, the Monte Carlo sampling errors are fairly low for all parameters. Therefore, the Gibbs sampler is run for 50.000 iterations. The first 20.000 iterations are the burn-in samples. Inferences are based on the last 30.000 iterations.

4.5.1 Measurement Model Analysis

Hierarchical confirmatory factor analysis is used to estimate a model composed of fifteen first-order and six second-order, latent factors. This fully disaggregated

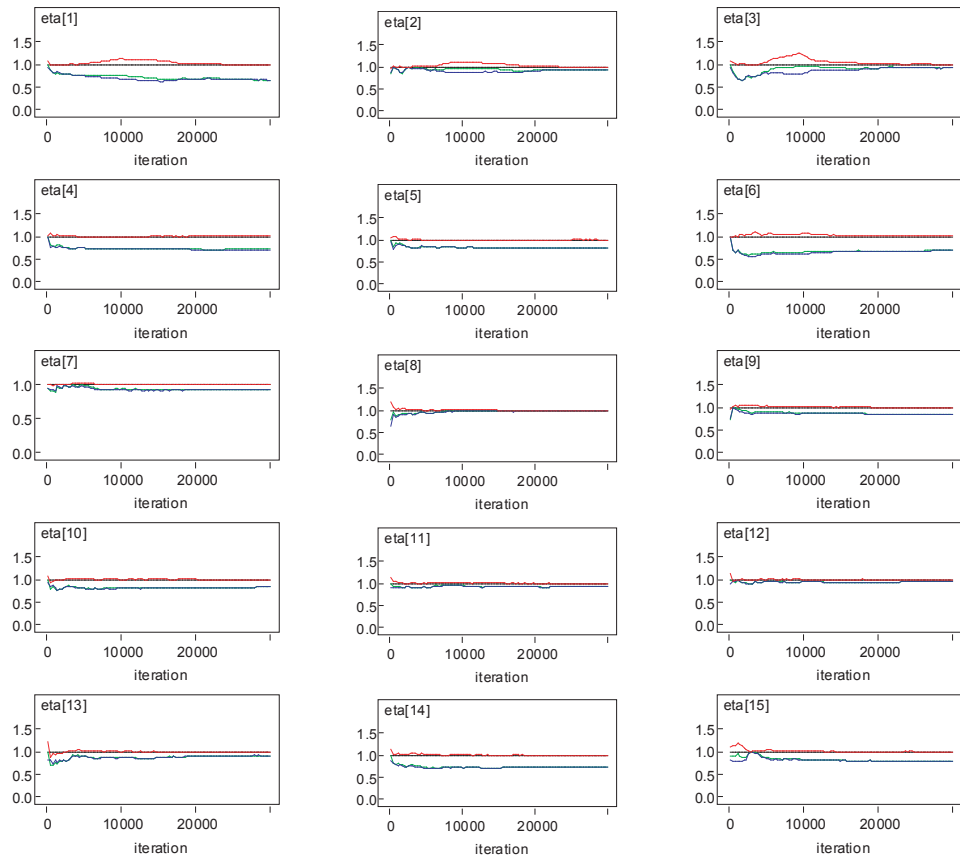
Dimension			mean	sd	2.5%	median	97.5%
	Subdimension						
CUSTDC	cusdc_ig	eta	0.204	0.102	0.025	0.200	0.413
	cusdc_id	eta	0.283	0.093	0.080	0.286	0.456
	custdc_resp	eta	0.273	0.109	0.044	0.277	0.479
COMDC	comdc_ig	eta	0.309	0.070	0.165	0.310	0.444
	comdc_id	eta	0.422	0.083	0.243	0.425	0.574
	comdc_resp	eta	0.465	0.084	0.298	0.467	0.620
SUPPDC	suppdc_ig	eta	0.368	0.132	0.072	0.383	0.591
	suppdc_id	eta	0.332	0.138	0.045	0.340	0.596
	suppdc_resp	eta	0.230	0.124	0.017	0.223	0.485
TMC	tmc_ig	eta	0.555	0.088	0.380	0.556	0.723
	tmc_id	eta	0.687	0.093	0.486	0.693	0.854
CRC	crc_is	eta	0.273	0.110	0.043	0.281	0.467
	crc_coop	eta	0.249	0.117	0.033	0.248	0.482
SRC	src_is	eta	0.391	0.118	0.106	0.402	0.594
	src_coop	eta	0.395	0.131	0.098	0.410	0.612
	Items		mean	sd		mean	sd
CUSTDC	custdc_ig	lambda	1.000		precision	0.745	0.131
	cusdc_ig	lambda	1.066	0.300	precision	0.658	0.123
	custdc_id	lambda	1.019	0.304	precision	0.686	0.126
	custdc_id	lambda	1.000		precision	0.732	0.108
	custdc_id	lambda	1.221	0.229	precision	0.500	0.104
	custdc_id	lambda	0.777	0.186	precision	0.792	0.108
	custdc_resp	lambda	1.000		precision	0.659	0.110
	custdc_resp	lambda	1.034	0.228	precision	0.601	0.108
	custdc_resp	lambda	0.896	0.203	precision	0.698	0.106
	comdc_ig	lambda	1.000		precision	0.745	0.100
COMDC	comdc_ig	lambda	1.355	0.157	precision	0.253	0.053
	comdc_ig	lambda	1.254	0.148	precision	0.357	0.059
	comdc_id	lambda	1.000		precision	0.296	0.060
	comdc_id	lambda	0.909	0.096	precision	0.381	0.066
	comdc_resp	lambda	1.000		precision	0.391	0.072
	comdc_resp	lambda	0.923	0.114	precision	0.440	0.071
	comdc_resp	lambda	1.051	0.114	precision	0.279	0.060
	suppdc_ig	lambda	1.000		precision	0.353	0.057
	suppdc_ig	lambda	1.116	0.100	precision	0.203	0.050
	suppdc_ig	lambda	1.017	0.099	precision	0.345	0.057
SUPPDC	suppdc_id	lambda	1.000		precision	0.435	0.086
	suppdc_id	lambda	0.961	0.146	precision	0.526	0.093
	suppdc_resp	lambda	1.000		precision	0.499	0.089
	suppdc_resp	lambda	1.023	0.161	precision	0.537	0.097
	tmc_ig	lambda	1.000		precision	0.253	0.052
	tmc_ig	lambda	1.127	0.098	precision	0.060	0.051
	tmc_re	lambda	1.000		precision	0.011	0.021
	tmc_re	lambda	0.853	0.051	precision	0.278	0.039
	crc_is	lambda	1.000		precision	0.588	0.085
	crc_is	lambda	1.236	0.161	precision	0.329	0.072
CRC	crc_is	lambda	1.138	0.157	precision	0.429	0.076
	crc_coop	lambda	1.000		precision	0.450	0.078
	crc_coop	lambda	1.049	0.136	precision	0.394	0.076
	crc_coop	lambda	0.640	0.134	precision	0.772	0.104
	src_is	lambda	1.000		precision	0.404	0.076
	src_is	lambda	1.033	0.131	precision	0.370	0.076
	src_coop	lambda	1.000		precision	0.447	0.072
	src_coop	lambda	1.335	0.145	precision	0.041	0.068

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 4.1: Parameter Estimates

measurement model with all observed variables allows us to test the convergent and discriminant validity. Note that one loading for each factor is fixed to unity in order to identify the model and to set a metric or scale for the factors (Marsch and Hocevar 1985).

A fundamental notion in confirmatory factor analysis is the assessment of fit. Scheines et al. (1999) suggest the use of posterior predictive p-values (Gelman, Meng and Stern, 1996; Rubin, 1984) to evaluate the likelihood ratio goodness-of-fit statistic. Model fit is assessed by comparing the observed $T(\Sigma)$ to the distribution of $T(\Sigma^{rep})$, where Σ^{rep} denotes replicated values of Σ . A summary of this comparison is given by the posterior predictive p-value, the probability that $T(\Sigma^{rep}) \geq T(\Sigma)|\Sigma$. Small p-values indicate implausibility of the data under the model (Berkhof, van Mechelen and Hoijtink 2000). In other words, small p-values suggest a lack of fit of the model to the data. The proposed model adequately represents the data since



eta[1] is custdc_ig, eta[2] is custdc_id, eta[3] is custdc_resp, eta[4] is comdc_ig, eta[5] is comdc_id, eta[6] is comdc_resp, eta[7] is suppdc_ig, eta[8] is suppdc_id, eta[9] is suppdc_resp, eta[10] is tmc_ig, eta[11] is tmc_r, eta[12] is crc_is, eta[13] is crc_cp, eta[14] is src_is, eta[15] is src_cp.

Figure 4.2: The estimated potential scale reduction (EPSR) value

a check criterion, which compares a replicated mean error sum of squares with the observed one, of .07 is obtained. By this standard, the model fits the data.

The results are shown in table 4.1. To avoid clutter, only the posterior mean and standard deviations of the eta's, lambda and precision over the 30.000 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. The most fundamental part of our model are the eta's, the parameters that relate the second-order factors to their corresponding lower-order factors. For the eta's we plot the sample path of the Markov Chain Monte Carlo algorithm in figure 4.2. The plots show that the eta's are already converged before 20.000 iterations. Furthermore, the posterior distributions for these parameters are in general symmetric (the frequency estimates are approximately normal). Noteworthy is that the standard deviations of the customer-relating capabilities dimensions are relatively high. In general, the previously outlined results provide support for

Model	deviance	DIC
Proposed factor structure	12330	13450
CM I: one-factor model	15240	15450
CM II: two-factor model	14750	15040
CM III: six-factor model	13020	13710
CM IV: fifteen first-order factor model	12460	13480
CM V: CM III plus one second-order factor	13020	13720
CM VI: CM III plus two second-order factor	13010	13720
CM VII: CM IV plus one second-order factor	12440	13470
CM VIII: CM IV plus two second-order factor	12390	13120

Table 4.2: Model Comparison: Deviance Information Criterion

our proposed model. To further investigate the strength of this model we compare it to several other previously discussed competing models.

4.5.2 Model Comparison and Choice

Besides the proposed factor structure for our strategic marketing capabilities construct, eight theoretically plausible competing models are fitted to the 38 selected indicators to determine the model that most appropriately represents the covariance matrix. To determine the best fitting model, we use both the deviance information criterion and Gelfand and Ghosh's criterion.

Concerning the deviance information criterion, the deviance value converged rapidly in less than 1.000 iterations. The results of the proposed model and the competing models are provided in table 4.2. Non of the competing models show better deviance statistics than our proposed model. Concerning the deviance information criterion (DIC), only competing model VIII, the fifteen first-order and two second-order factor model, shows relatively a better fit than our proposed model. The reason for this is the effective number of parameters in model VIII. This number is smaller for model VIII than for the originally proposed factor structure. Furthermore, table 4.2 shows that the simple (nonhierarchical) factor structures have the highest value for DIC.

To further analyze the relative strength of our proposed factor structure, we calculate Gelfand and Ghosh's criterion (GGC). Noteworthy is that this value converged immediately. By comparing the results of each model, as shown in table 4.3, we see that the GGC value, via mean of MSPE, prefers the factor structure origi-

Model	MSPE				
	mean	sd	2.5%	median	97.5%
Proposed factor structure	1.556	0.040	1.48	1.556	1.637
One-factor model	3.023	0.102	2.835	3.019	3.233
Two-factor model	2.335	0.051	2.237	2.335	2.438
Six-factor model (SFM)	1.718	0.041	1.64	1.718	1.799
SFM + one second-order factor	1.717	0.041	1.638	1.716	1.796
SFM + two second-order factor	1.715	0.040	1.638	1.715	1.796
Fifteen-factor model (FFM)	1.585	0.041	1.507	1.585	1.666
FFM + one second-order factor	1.577	0.040	1.5	1.577	1.658
FFM + two second-order factor	1.573	0.040	1.496	1.572	1.654

Table 4.3: Model Comparison: Gelfand and Ghosh Criteria

nally proposed for our strategic marketing capabilities model. The simple models show relatively high values for MSPE. The MSPE value for both model VII and VIII is close to that of the proposed model, which indicates that complex models of strategic marketing capabilities are formally more appropriate than simple ones.

In summary, both the DIC and MSPE statistics demonstrate that the proposed factor structure for our strategic marketing construct represents the variance-covariance matrix relatively best. The two criteria (deviance and MSPE) demonstrate good convergence properties in our case. In short, these results validate our proposed model.

4.6 Discussion

The marketing concept has its origin in the 1950s and some scholars argue that now is the time to define a more sophisticated concept. Webster (1994) argues that most of the assumptions of the marketing concept are no longer appropriate in today's highly competitive markets. An accepted recent perspective is that relationship marketing is also fundamental in serving customers and generating market-based advantage (e.g., Achrol and Kotler 1999; Day and Montgomery 1999; Webster 1992). A recent attempt to integrate the classical market orientation with the relationship marketing perspective, although implicitly, is Srivastava, Shervani and Fahey's (1998) concept of market-based assets. Srivastava et al. (2001) divide market-based assets in two related types: relational and intellectual. A more classical work is that of Lusch and Lucznik (1987) and Day (1994). These studies, however, do not consider explicitly and justify the integration of both market orientation and relationship marketing. Building on the previous work, we develop a model, called the strategic marketing capabilities construct, integrating both the market orientation and the relationship marketing direction. On the basis of prior research, we develop a hierarchical classification of strategic marketing capabilities. To estimate this model appropriately we utilize a Bayesian framework. Furthermore,

we investigate two model comparison procedures in our case, the deviance information criterion and Gelfand and Ghosh criteria. The findings support the emerging perspective integrating both the market orientation and relationship marketing literature. The results described in the previous section highlight some of the unique insights that emerge from this integrative research approach.

4.6.1 Strategic Marketing Capabilities

Our findings are in line with our proposition. In this study, the DIC statistic supports our proposed factor structure for the strategic marketing capabilities model. However, one of the competing models indicates a better fit to the covariance matrix than our proposed model. Despite this, we choose our proposed model as the most appropriate model. First, the Gelfand and Ghosh's criterion shows the best fit for the proposed factor structure; actually, GGC is a more formal approach to model choice than Spielhalter et al.'s (2002) procedure. Second, taking a pragmatic perspective, following Gelman and Rubin (1995, p. 171), who state that "we believe selection to be relatively unimportant compared to the task of constructing realistic models that agree with both theory and data. In summary, we would prefer to fit a complicated model, using Bayesian methods—but not BIC—and then summarize it appropriately to answer the substantive questions of interest." we believe that our model is more meaningful. In other words, our second justification for choosing the proposed model is based on the GGC statistic and the meaningfulness of the results.

Since our primary goal is to develop an integrated model incorporating both market orientation and relationship relating components and to investigate whether the proposed factor structure (and hence the proposed model) adequately fits the data, we do not conduct a purification stage by eliminating the least aligned indicators. Further refinements of the strategic marketing capabilities construct are essential to make the model agree better with the observed data. By saying this, we encourage researchers to further refine the dimensions of the strategic marketing capabilities construct. Several points of improvement may be identified. For example, the standard deviations of the customer-relating capabilities dimensions are relatively high. This suggests that the customer-relating capabilities factor does not fit (into) the model as others do. Other dimensions that need some additional care are the customer-driven capabilities dimensions.

The strategic marketing capabilities construct developed in this study 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 in sensing and relating to the market. Our results may have implications for the business-to-business industry. Perhaps the main implication of this study is that it identifies the importance of both the development of a market-sensing and market-relating strategy, especially for wholesalers. This suggests that management or marketing employees have to consider these two perspectives when developing a marketing strategy.

4.6.2 Bayesian Confirmatory Factor Analysis

A major disadvantage of classical methods used in estimating confirmatory factor analytical models, such as maximum likelihood, generalized least squares and weighted least squares, is their use of the asymptotic theory. Therefore, proper statistical inferences are only made when the sample size is (very) large. In the case of a rather small sample size, as in our case, it is frequently reported that the behavior of maximum likelihood, generalized least squares and weighted least squares is not robust for obtaining proper parameter estimates. A strong alternative, especially in the case of small sample sizes, is the Bayesian framework (see for example the findings of Lee and Song 2004). The advantage of the Bayesian framework in model estimation and testing is generally known (see for a detailed discussion, Rossi and Allenby 2003). In the Bayesian approach Markov Chain Monte Carlo samples are taken from the true posterior regardless of the sample size (Scheines et al. 1999). As a consequence, the standard errors calculated from Markov Chain Monte Carlo samples are more reliable. In this study, we could easily calculate even the rather complex six second-order and fifteen first-order factor model. The parameters, in general, show good convergence properties. Utilizing the classical methods in estimating and testing confirmatory factor analysis, we would not have been able to estimate the proposed and the competing models. The case of more parameters than sample size occurs and these (classical) methods then collapse. Based on this, we recommend researchers to utilize the Bayesian approach in estimating and testing a confirmatory factor analytical method, especially in the case of small sample sizes and complex factor structures. However, we acknowledge that the classical methods, because of the available software, are more simple to use than their Bayesian counterpart. Therefore, we encourage the development of user-friendly Bayesian analysis software for applied researchers to estimate (complex) factor analytical models.

4.6.3 Model Choice

In confirmatory factor analysis, model selection is a fundamental activity. In this study we use two criteria: (1) deviance information criterion (DIC), and (2) Gelfand and Ghosh Criterion (GGC). To the author's knowledge, these criteria have not been (fully) examined in the case of confirmatory factor analysis. Results from this study indicate that these procedures can be usefully applied to empirical studies.

In general, the DIC procedure shows good properties in our case. It points out that the less likely models have the highest score. To empirically derive conclusions based on this criterion, it is fundamental to investigate whether the signs of the DIC values are positive (in all cases). A major problem of this statistic is the negative value generated for the number of effective parameters. We have explicitly monitored this problem, especially in the case of hierarchical factor structures. As our analysis indicate, this problem did not occur. Furthermore, the deviance value converged rapidly in less than 1.000 iterations. Based on the previous, we believe that the DIC procedure is suitable in both hierarchical and nonhierarchical confirmatory

factor analysis. In saying this, we acknowledge that further research is needed to determine whether DIC offers a strong framework for comparison and evaluation in the case of (non)hierarchical confirmatory factor analysis.

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

4.7 Limitations

The findings in this study are encouraging in suggesting the (potential) value of an integrated model of marketing. However, there are some limitations to our work. A limitation is the national character of our sample. This study needs to be extended to an international context. By doing so one needs to consider international aspects of measurement equivalence.

Also a limitation is the investigation of only one single industry, wholesaling. This study uses a sample of Dutch wholesalers and the findings cannot be completely generalized to other settings and countries. Although we believe that our construct is especially suitable in a business-to-business environment, research examining other settings could further enhance our knowledge about the composition of strategic marketing capabilities. We speculate that our model is rather generic for the services setting. However, from a manufacturer perspective other strategic marketing capabilities could also be identified (see for example, Miller and Roth 1994). Hence, further research should be conducted to develop measures of strategic marketing capabilities suitable for a whole range of industries. Hence, further research is needed examining the strategic marketing capabilities construct in other settings.

4.8 Future Research Directions

Further research is needed, in part because of the limitations of our study. In terms of possible future research directions, several fruitful areas can be offered. Further research aimed at better understanding possible antecedents of strategic marketing capabilities may be a very promising avenue of research. An interesting avenue of research would be the investigation of organizational factors (i.e., formalization and centralization), human resources factors (i.e., recruitment, behavioral-based evaluation and reward, empowerment and training) and firm strategy (Frambach, Prabhu, Verhallen, 2003) as antecedents of strategic marketing capabilities. Furthermore, culture may play a role as an independent variable. We speculate that firms with cultures that are relatively responsive (market culture) and flexible (adhocracy culture) have stronger strategic marketing capabilities than consensual (clan culture) and bureaucratic (hierarchical) cultures.

Further research is needed investigating the effect of strategic marketing capabilities on firm performance. Do these capabilities affect business financial performance? Is this a linear effect? Is this relationship mediated by other variables, such as customer satisfaction and innovativeness? Is this relationship moderated by other variables?

Another possible fruitful direction is to investigate the moderating effect of strategy type on the (our proposed) strategic marketing capabilities-business performance relationship (see for studies relating the effects of strategy type on the market orientation-performance relationship, Matsuno and Mentzer 2000; McKee, Varadarajan and Pride 1989).

The study of possible mediators of the strategic marketing capabilities-customer satisfaction link is yet another avenue for interesting research. For example, is the strategic marketing capabilities-customer satisfaction relationship mediated by other variables? Han, Kim and Srivastava's (1998) findings indicate that the customer orientation-performance link is mediated by innovativeness. Therefore, we speculate that the relationship between strategic marketing capabilities and customer satisfaction could be mediated by innovativeness. However, is this relationship partially mediated or fully mediated by innovativeness? Further research is needed to clarify these issues.

4.9 Conclusions

The goal of this study is to provide a first step in developing an integrated model of marketing. Our results suggest that the proposed model has good psychometric properties. This leads us to conclude that an integrated model of marketing enhances our understanding of marketing. Taking the importance of an integrated model of marketing, we suggest that future research including this view and further developing and refining this model is necessary. We hope that we have contributed to this perspective.