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Accounting for Unobserved Heterogeneity in the Analysis of Antecedents and Consequences of Corporate Reputation: An Application of FIMIX-PLS

Abstract

The following contribution presents a novel response-based approach, finite mixture partial least squares (FIMIX-PLS), with which to classify data based on the heterogeneity of the estimates in the inner path model. Subsequently the approach is applied to a previous study by Eberl (2008) that analyses the stakeholder-specific relationships between customer satisfaction, customer loyalty and corporate reputation as well as its drivers. This new approach opens the way for reliable identification of distinctive customer segments and their characteristic estimates regarding the latent relationships between variables in the inner model. Our analysis demonstrates that an aggregate analysis can be seriously misleading and, thus, provide a strong case for segment-specific reputation management analysis.

Keywords: Partial Least Squares, Latent Classes, FIMIX-PLS, Corporate Reputation

Track: Marketing Research and Research Methodology

1. Introduction

In a recent study, Eberl (2008) evaluates the effects of corporate-level marketing activities on customer satisfaction and loyalty via the mediating construct corporate reputation, which is conceptualized two-dimensionally in accordance with Schwaiger (2004). Eberl (2008) applies partial least squares multi-group analysis (PLS-MGA; Chin & Dibbern, 2008) to empirically test for differences between several stakeholder groups in the German telecommunications industry (cp. Ringle, 2000). A key conclusion is that the affective dimension of corporate reputation is the most dominant function. In respect of the mobile communications market, this result implies that investments in a favourable assessment of corporate reputation's cognitive dimension (competence) do not necessarily result in an increase in customer satisfaction. Moreover, the study reveals that different stakeholder groups (media, politicians, financial community and the general public) assess a company's reputation and behaviour differently, which leads to marketing activities having varying effects on reputation. The findings make a strong case for the consideration of a priori information in the analysis.

Postulating homogenous segments based on prior knowledge usually provides unsatisfactory outcomes. Observable characteristics such as membership of a stakeholder group often gloss over heterogeneity (Wedel & Kamakura, 2000, p. 223), especially in the inner PLS path model estimates. In fact, heterogeneity is frequently unobservable and its source is usually unknown, which means that observations cannot easily be classified into sub-populations. Consequently, different approaches have recently been proposed to response-based clustering in a PLS path modelling framework. These procedures generalize decision tree (Sánchez, & Aluja, 2006), PLS typological regression (Squillacciotti, 2005, 2008; Trinchera, 2007), fuzzy regression (Esposito Vinzi, Trinchera, & Romano, 2007) and genetic algorithm (Ringle & Schlittgen, 2007) approaches regarding PLS path modelling. Developments in this line of research differ substantially in terms of covered types of heterogeneity, distributional assumptions and interpretability of the resulting segments. Nevertheless, the primary and most advanced response-based approach to segmenting data in a PLS framework is FIMIX-PLS. This methodology allows the simultaneous estimation of model parameters and segment affiliations of observations.

Our research applies FIMIX-PLS as a complementary analysis to the aggregate PLS path modelling results of Eberl's (2008) contribution. As the relationships between the different constructs are likely to vary by different unobservable respondent characteristics, we need to identify and to account for unobserved heterogeneity at the segment level. This investigation is a central requirement of PLS path modelling analyses. The interpretation of results on the aggregate data level can be seriously misleading if unobserved heterogeneity is not properly accounted for, thus causing erroneous inferences.

Answering the call of previous studies (Ringle, 2006; Esposito Vinzi, Ringle, Squillacciotti, & Trinchera, 2007), we apply FIMIX-PLS to a common marketing research problem in order to evaluate the methodology's capability to identify and treat unobserved heterogeneity in PLS path models. Consequently, the scope of this paper is exploratory.

2. Corporate reputation, its antecedents and consequences

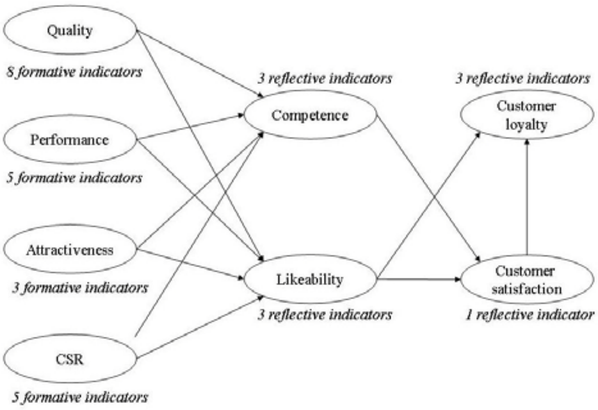
Owing to the growing sophistication and comparability of products and services as well as the increasing globalisation of different markets, intangible assets have become the focal point of marketing research and business practice: They offer high potential regarding differentiation and are hard to imitate (Hunt & Morgan, 1995, p. 8). Corporate reputation, defined as the "observers' collective judgements of a corporation based on assessments of the financial, social, and environmental impacts attributed to the corporation over time" (Barnett, Jermier, & Lafferty, 2006, p. 34), is a key intangible asset. Both academics and practitioners have delineated the various benefits of a high reputation. With regard to consumers, reputation functions as a risk-reduction mechanism (Kotha, Rajgopal, & Rindova, 2001, p. 573; Dowling, 2001, p. 12), leading to greater satisfaction (Aaker, 1991, p. 16) and loyalty (Selnes, 1993) and, thus, resulting in increased price premiums (Milgrom & Roberts, 1986, p. 817).

The construct of corporate reputation has been the subject of considerable research in the past few years, which has led to a wide variety of measurement approaches. According to Berens and van Riel (2004), these approaches can be categorized into three conceptual streams that distinguish different types of observer associations based on social expectations, corporate personality traits, or reasons to trust or distrust a company.

An important validity problem with prior reputation measurement approaches has always been that the reputation's multi-dimensionality has not been in accordance with the relevant conceptualization (Eberl & Schwaiger, 2005, p. 840). This critique holds specifically for Fortune's annual "Most Admired Companies" indices, which still rank among the most frequently used approaches. In keeping with the above definitional framework, Schwaiger (2004) defined corporate reputation as a two-dimensional, attitude-related construct. One dimension comprises all cognitive evaluations of the company ("competence"), whereas the second dimension captures affective judgements ("likeability"). Competence and likeability were individually operationalized by means of three indicators. These indicators were identified as exchangeable, and form a reflectively operationalized latent construct. Past research identified four exogenous driver constructs ("quality", "performance", "attractiveness" and "corporate social responsibility (CSR)"), which exhibit a very robust performance across different data sets, countries and industries (e.g., Schwaiger, 2004; Eberl & Schwaiger, 2005). The drivers feature a formative index operationalization by means of a total of 21 manifest variables that represent the levers of corporate-level marketing activities. Various studies have indicated that corporate-level marketing activities exert an influence on reputational judgements although, to date, there is very little empirical evidence as to whether these judgements affect a company's customer-specific marketing objectives (Eberl, 2005).

This study seeks to analyse the effect of corporate reputation and its drivers on two possible outcomes: customer satisfaction and customer loyalty. An identification of the segment-specific effects of reputation's cognitive and affective dimensions focuses on customer satisfaction and loyalty as well as its drivers. The results impart recommendations on segment-tailored marketing activities. In accordance with the analysis by Eberl (2008), it is hypothesized that the two dimensions of corporate reputation – as modelled by Schwaiger (2004) – relate to customer satisfaction, while likeability also directly influences customer loyalty. Customer satisfaction and loyalty employ reflective measures which are well known from empirical marketing studies (Zeithaml, Berry, & Parasuraman 1996). Figure 1 illustrates the path model.

Figure 1: Research model



3. Methodology

To uncover unobserved heterogeneity, we apply the FIMIX-PLS procedure (Ringle 2006, Ringle, Wende, & Will, 2005a, 2008), which combines the strengths of the PLS method with the advantages of classifying market segments according to finite mixture models. Based on this concept, FIMIX-PLS simultaneously estimates the model parameters and ascertains the heterogeneity of the data structure within a PLS path modelling framework.
In the first step of FIMIX-PLS, a path model is estimated by using the PLS algorithm and empirical data for manifest variables in the outer measurement models. The resulting latent variable scores in the inner path model are then employed to run the FIMIX-PLS algorithm in the second step. The segment-specific heterogeneity of path models is concentrated in the estimated relationships between latent variables. FIMIX-PLS captures this heterogeneity and calculates the probability of each observation so that it fits into each of the predetermined K numbers of segments. Assuming that each endogenous latent variable η_i is distributed as a finite mixture of conditional multivariate normal densities $f_{i|k}(\cdot)$, the segment-specific distributional function is defined as follows:

$$\eta_i \sim \sum_{k=1}^{K} \rho_k f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k), \tag{1}$$

where ξ_i is a exogenous variable vector in the inner model in respect of observation *i*, B_k is the path coefficient matrix of the endogenous variables and Γ_k of the exogenous latent ones, while Ψ_k depicts the matrix of each segment's regression variances of the inner model on the diagonal, zero else. The mixing proportion ρ_k determines the relative size of segment k (k=1,…,K) with $\rho_k > 0\ \forall k$ and $\sum_{k=1}^{K} \rho_k = 1$. Substituting $f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k)$ results in:

$$\eta_i \sim \sum_{k=1}^{K} \rho_k \left[\frac{|B_k|}{\sqrt[M]{2\pi}\sqrt{|\Psi_k|}} e^{-\frac{1}{2}(B_k\eta_i + \Gamma_k\xi_i)'\Psi_k^{-1}(B_k\eta_i + \Gamma_k\xi_i))} \right], \tag{2}$$

where M depicts the number of endogenous latent variables in the inner model. An EM-formulation of the FIMIX-PLS algorithm is used for statistical computations to maximize likelihood and to ensure convergence in this model.
When applying FIMIX-PLS to empirical data, the actual number of segments K is usually unknown. In the light of problems that arise when applying hypothesis tests in a finite mixture model framework (Frühwirth-Schnatter, 2006, p. 99), researchers frequently revert to a heuristic approach, e.g., by building on information or classification criteria. In the past, a huge number of different criteria have been developed to assess the number of segments. All these criteria have different theoretical underpinnings and statistical properties (for a review of the most frequently applied measures, cp. Oliveira-Brochado & Martins, 2005).

4. Data & Results

The PLS path model analysis draws on four major service providers in Germany's mobile communications market, including two large providers who had a combined market share of more than 74% in 2005 (Bundesnetzagentur, 2007). Data were collected by means of CATI interviews in February 2005. Each respondent rated reputation and driver construct indicators on seven-point Likert scales. Satisfaction and loyalty were surveyed in respect of the interviewees' own service providers. The survey also tested several socio-demographic characteristics. The dataset comprises N=344 subjects.
Table 1 provides an overview of the aggregate PLS path coefficients in the models, FIMIX-PLS results in respect of two segments, the mixing proportions of each segment π_s, the R^2 value of each latent endogenous constructs and GoF measures (cp. Tenenhaus, Esposito Vinzi,

Chatelin, & Lauro, 2005, p.173). To test the significance of the differences between the path coefficients, we followed Chin's (2000) PLS-MGA approach and carried out pair-wise t-tests, based on standard errors derived from a bootstrapping procedure (500 subsamples, 344 cases, individual sign change). Kolmogorov-Smirnov-, F-tests results regarding the equality of standard errors and Cronbach's α values suggest that all prerequisites for multi-group comparison have been met. The resulting p[mgp]-values for path differences are presented in Table 1.

Table 1: Analytical Results

Data analysis strategy	**Global**	**FIMIX**		
		s=1	s=2	p[mgp]
quality → competence	.455**	.505**	.511**	.486
performance → competence	.297**	.071	.406**	.007
attractiveness → competence	.086	-.220**	.267*	.000
CSR → competence	.024	.407**	-.293**	.000
quality → likeability	.397**	.313**	.499**	.135
performance → likeability	.119	-.130	.287**	.002
attractiveness → likeability	.163**	.192**	.114*	.270
CSR → likeability	.165**	.205**	.075*	.108
competence → customer satisfaction	.127*	-.201**	.388**	.001
likeability → customer satisfaction	.452**	.437**	.350**	.303
customer satisfaction → customer loyalty	.502**	.415**	.615**	.028
likeability → customer loyalty	.345**	.334**	.308**	.411
π_s	1	.337	.663	
R^2 (competence)	.631	.715		
R^2 (likeability)	.558	.615		
R^2 (customer satisfaction)	.293	.380		
R^2 (customer loyalty)	.556	.607		
GoF	.579	.607		

* significance at p<.10 ** significance at p<.05

Using the software application SmartPLS (Ringle, Wende, & Will, 2005b), FIMIX-PLS is applied to the data, using consecutive numbers of segments k and ten replications. The adequate model (i.e. the number of segments) is chosen according to the minimal value of the heuristic measure "Consistent Akaike's Information Criterion", which has been suggested as working well with FIMIX-PLS (Sarstedt & Salcher, 2007). According to the results, the two-segment solution is appropriate. This is supported by the distribution of the posterior probabilities of segment membership where more than 80% of all observations are assigned to one of the two segments with $\rho_{ik} \geq .7$. To estimate the segment-specific path coefficients in the measurement models, observations are assigned to each segment according to the segment membership's maximum a posterior probability.

In the next step, we use the decision tree algorithm by Biggs, de Ville and Suen (1991) to identify an explanatory variable that best describes the uncovered segments. This analysis reveals that segment one represents customers of the smaller mobile service providers who live in single or large households. Segment two consists of customers of the two larger mobile providers and medium-sized household customers of small providers. Based on this classification, it is possible to obtain standard segment-specific PLS path model estimates.

The GoF value (.579) as well as the R^2 values of the constructs competence, likeability and customer loyalty are fully acceptable in terms of the global model. The relatively low outcomes regarding satisfaction are not surprising. Intangible assets (e.g., corporate reputation) represent only one of the numerous determinants of customer satisfaction. The global model results clearly indicate that the affective dimension not only dominates, but also has a great impact on customer satisfaction and loyalty. Competence, on the other hand, has a significant ($p<.10$) but relatively small effect on satisfaction. This result is plausible as product differentiation in this market almost exclusively derives from feelings or sentiments due to the product's intangibility.

According to the FIMIX-PLS results, all endogenous constructs have increased R^2 values, ranging between 9% (customer loyalty) and 30% (customer satisfaction) higher than in the global model. Compared to a stakeholder group-specific analysis by Eberl (2008), improvements in model fit range between 2% (likeability) and 25% (customer satisfaction). With a value of .607, the GoF is at a highly satisfactory level when compared to common analysis results. It is remarkable that almost all inner model relationships are significant at $p<.05$. Unlike the global model, both segment-specific results provide evidence of a substantial and varying relationship between competence and customer satisfaction. This path is negatively affected by perceived competence in the smaller segment and positively influenced in the larger segment. Nevertheless, to enhance customer satisfaction and loyalty, the industry should address the affective dimension as the main driver.

However, it is important to note that both segments differ considerably with regard to the drivers of this dimension. In segment one, CSR, attractiveness and quality positively influence likeability while performance exerts a negative effect. In the other segment, quality is the main driver of likeability, whereas the effect of CSR can be disregarded. Consequently, management has to conduct segment-specific marketing activities by either addressing the perception of the quality and CSR construct (segment one) or the quality and performance construct (segment two). Overall, the relationships differ substantially between the constructs, with sign changes appearing in some paths, so that an aggregate analysis results in flawed management implications.

5. Conclusion

The identification of different groups of consumers with distinct estimates in the inner path model constitutes a critical issue for the application of path modelling methodology to shape effective marketing strategies. Our contribution extends the previous study by Eberl (2008) by applying FIMIX-PLS to allow for unobserved heterogeneity in inner model path estimates. This new approach permits reliable identification of distinctive customer segments as well as their characteristic estimates regarding latent relationships between variables in the inner model.

Our analysis demonstrates that an aggregate analysis can be seriously misleading. We make a strong case for further differentiated, segment-specific reputation management analysis, since our analysis arrives at considerably higher model fit in this example. By accounting for unobserved heterogeneity, we provide a more complete picture of the effects of antecedents and drivers of corporate reputation. The results exhibit the complementary analytic potentials of FIMIX-PLS that are particularly relevant and a requirement for customer segmentation tasks in PLS path modelling. Segmenting consumer response along multiple dimensions should lead to a richer understanding of the impact of the marketing mix and allows for the formulation of effective marketing strategies. Therefore, we believe that FIMIX-PLS will assume an imperative role in enhancing PLS in the next wave of analytical procedures.

Further research will require the extensive use of FIMIX-PLS on marketing examples. Alternative ways should be developed to identify explanatory variables that best characterize the assignment of observations. Experience has shown that existing procedures such as decision tree approaches, logit analyses, or the diagnosis approach by Ramaswamy, DeSarbo, Reibstein and Robinson (1993) rarely help to reveal the segments identified by FIMIX-PLS.

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