

University of Groningen

Market-based capabilities, perceived quality and firm performance

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Document Version

Publisher's PDF, also known as Version of record

Publication date:

2006

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Aakouk, M. (2006). *Market-based capabilities, perceived quality and firm performance*. [Thesis fully internal (DIV), University of Groningen]. s.n.

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Chapter 6

Development and Assessment of the WholeSaleQual Construct

Abstract This paper describes the development of an instrument, which we call WholeSaleQual, for assessing customer perceptions of quality in a wholesale environment. In developing this construct, we integrate several scales from the quality literature, which are largely investigated independently in the past. The purpose of this paper is to (1) describe the development of a model for measuring quality in a wholesale setting, (2) compare the developed construct with a hierarchical model, and (3) investigate an operational level model, by estimating the relative importance of the quality attributes, using partial least squares regression. Factor analytical methods suggest that the originally proposed nonhierarchical model better represents the variance-covariance matrix than the hierarchical model. Furthermore, it seems that organizations excel when they are able to deliver superior quality to their customers. Also, the applied methodology may help managers faced with the problem of how to trade off competing quality improvement initiatives. We consider the research and managerial implications of this study.

6.1 Introduction

During the past decade, there has been a growing stream of research exploring the construct of quality. Studies in this area have addressed conceptual issues (e.g., Grönroos, 1984; Parasuraman, Zeithaml and Berry, 1985), measurement issues (e.g., Brady and Cronin, 2001; Parasuraman, Zeithaml and Berry, 1988, 1991, 1994) and consequences of quality (e.g., Zeithaml, Berry and Parasuraman, 1996). Although considerable progress has been made, these streams of research have been among the most debated in services marketing. For example, Brady and Cronin (2001) argue that little advance has been made “to what should be measured” (p. 34).

The growing body of research on quality in marketing is largely conducted by surveying or interviewing customers (end-users) in a retail setting (e.g., Babakus and Boller, 1992; Brown, Churchill and Peter, 1993; Carman, 1990; Cronin and Taylor, 1992; Parasuraman et al., 1988). Several authors have attempted to expand the theoretical domain of service quality to include other settings by introducing integrative, more complex, (hierarchical) models (c.f., Brady and Cronin, 2001; Bienstock, Mentzer, and Bird, 1997; Dabholkar, Shepherd and Thorpe, 2000; Holmlund and Kock, 1995; Mentzer, Flint and Kent, 1999; Mentzer, Flint and Hult, 2001; Rust and Oliver, 1994). However, this stream of research has neglected to investigate a thor-

ough business-to-business model of quality. This neglect is notable because these studies do not tell a complete story. A notable exception is Mentzer et al. (2001), who integrate logistics, information and service attributes to develop their logistics service quality construct. Their main thesis is that service quality is important, but provides little insight into issues relevant in a business-to-business setting, such as the delivered product, logistics and information. In the same spirit, Westbrook and Peterson (1998) state that despite the growing interest in the business-to-business sector, little research has been conducted measuring or developing a specific quality measure for this sector. They argue that in these settings, the evaluation of quality is much more complex. Therefore, they call for further investigation of the underlying determinants of quality for business-to-business companies.

Following recent literature suggesting the appropriateness to develop sector specific quality models (Carman, 1990; Mentzer et al., 2001), this paper develops a quality model for wholesaling. In this service setting, the combinations of delivered services and products, and offered logistics and information, comprise the value added to customers. Following Mentzer et al. (2001) we propose a nonhierarchical quality model for wholesaling. This concerns a simple model where all dimensions, which are related to service quality (e.g., Parasuraman et al., 1985), logistics service quality (e.g., Mentzer et al., 2001), product quality (e.g., Rust and Oliver, 1994), and information quality (e.g., Maltz and Kohli, 1996), are given equal weight and treated as if they occur simultaneously. We also investigate whether a hierarchical quality model is a better representation of quality in a wholesale setting. This competing model has the following higher-order dimensions: (1) service quality, (2) product quality, (3) logistics service quality, and (4) information quality. These four dimensions have different subdimensions, which are derived from previous research.¹

In this study we do not only develop a quality construct for wholesaling, but go a step further by relating operational quality perceptions (dimensions of the proposed WholeSaleQual construct and subdimensions of the competing hierarchical model) to customer satisfaction. We refer to this modeling approach, following Soteriou and Chase (2000), as an “operational level analysis.” This approach enables us to derive potential points for improvement. In general, the problem of an operational level analysis is the occurrence of several statistical problems, such as the problem of multicollinearity and small sample size, that may influence or limit the significance of the outcomes, especially when applying standard multiple linear regression, which is largely utilized and recommended in the quality literature. To analytically derive concrete information we utilize partial least squares regression (PLSR). This algorithm has many advantages when considering an operational level analysis (see for example, chapter 3 in this dissertation; Martens and Martens, 2001).

In this chapter we report the results of two studies. In study 1, we introduce and describe the development of the WholeSaleQual construct. We investigate two plausible factor structures of WholeSaleQual: (1) a nonhierarchical model, and (2) a hierarchical model. We find that a nonhierarchical operational quality model,

¹Note that these subdimensions all become first-order factors in the nonhierarchical model.

where all dimensions contribute equally to quality, fits the data better than a model with a hierarchical structure. In study 2, we relate our operational quality model to customer satisfaction. In doing so, we use both PLSR and ordinary least squares regression (OLS). Our results suggest that several quality attributes explain customer satisfaction. Furthermore, PLSR provides a good estimation method to derive fruitful conclusions, given the high multicollinearity in our dataset, whereas OLS fails to extract valuable outcomes.

6.2 WholeSaleQual Construct (Study 1)

6.2.1 Introduction

Today, service firms focus on customer perceived quality as a key to financial success. However, there is a lot of heterogeneity between service firms. For example, unlike banks, wholesalers offer logistics and physical products. Therefore, findings of several marketing researchers suggest the development of sector specific quality models (e.g. Carman, 1990; Dabholkar et al., 1996; Mentzer et al., 2001). In this study, we develop a quality model for the wholesale industry, one of the major industries in the western economy, which we call WholeSaleQual.

6.2.2 WholeSaleQual

The main purpose of wholesalers is to deliver the right amount of the right product at the right place at the right time in the right condition at the right price with the right information (Coughlan et al., 2000). This suggests that wholesalers create value through services, products, logistics and information. Hence, to investigate the degree to which a wholesaler is able to deliver quality, one has to investigate the offered services, products, logistics and information simultaneously. Therefore, we propose and develop a new quality construct for wholesaling with dimensions related to: service quality (e.g., Parasuraman et al., 1985), logistics service quality (e.g., Mentzer et al., 2001), product quality (e.g., Gronroos, 1982; Rust and Oliver, 1994), and information quality (e.g., Maltz and Kohli, 1996).

In developing our WholeSaleQual model, we could choose between two plausible factor structures: (1) nonhierarchical, and (2) hierarchical. A nonhierarchical factor structure suggests that all dimensions contribute equally to the model (see for example research in the field of service quality, Parasuraman et al., 1985, 1988; Mentzer et al., 2001). Other researchers prefer the examination of hierarchical conceptualizations of quality (for example, Brady and Cronin, 2001; Dabholkar, Thorpe and Rentz, 1996). Their main thesis is that a complex conceptualization better represents the dynamics of the market.

Following the main stream in this research field, we propose a nonhierarchical structure of quality. Hence, we argue that customers indeed break several dimensions, related to service, product, logistics and information, into various dimensions. Furthermore, we investigate whether this factor structure outperforms more complex ones.

hypothesis 1 a nonhierarchical conceptualization of WholeSaleQual is a better representation of the variance-covariance matrix than a hierarchical conceptualization of WholeSaleQual.

6.3 Method

As described previously, our WholeSaleQual construct has eighteen factors. These factors relate to: (1) service quality, (2) product quality, (3) logistics service quality, and (4) information quality. Scales of the factors we examine are available in the literature or could be easily derived from previous work. Next, we provide a small overview.

6.3.1 Service Quality

Service quality is one of the most studied qualitative measures of performance. Several conceptualizations of service quality are introduced in the literature. SERVQUAL, the most examined model, assesses customer perceptions of service quality in retailing organizations (Parasuraman et al., 1985). After the work of Parasurman et al. (1988), who measured perceived service quality as the difference between perceived service and expected service, researchers begin to examine the validity of SERVQUAL across different industrial settings (Carman, 1990; Babakus and Boller, 1992; Brown, Churchill and Peter, 1993). These researchers find that the computed disconfirmation has a poor model fit and suggest to combine perceptions and expectations into a single scale. Grönroos' model (1984), like SERVQUAL, has its roots in the disconfirmation perspective, and hence, is subjected to the same measurement critic as the Parasuraman et al. (1988) model. Based on the previously mentioned findings, Cronin and Taylor (1992) propose an alternative method of operationalizing perceived service quality, called SERVPERF. The results of Cronin and Taylor (1992) show that their SERVPERF approach might be an improved means of measuring the service quality construct. After their work, many other researchers provide support for the performance-based measure of service quality (e.g. Dabholkar et al., 2000). Therefore, we use SERVPERF to measure service quality. Hence, we have the following components of service quality: (1) reliability, (2) responsiveness, (3) assurance, (4) empathy and (5) intangibles.

6.3.2 Product Quality

Product quality refers to the technical quality of the product that is delivered. Concerning the conceptualizations of product quality, several scales/ constructs have been developed in the (marketing) literature (Sousa and Voss, 2002; Stone-Romero, Stone and Grewal, 1997). Fornell, Johnson, Anderson, Cha and Bryant (1996) conceptualize perceived quality in two components of consumption experience: (1) reliability, and (2) customization. They define customization as the degree to which the firm's offering is customized to meet heterogeneous customer needs. Reliability

refers to the degree to which the firm's offering is reliable, standardized, and free from deficiencies. In this study, building on the marketing dominated product quality literature, we add two important dimensions of product quality (see also Mentzer et al., 2001): (3) product availability, and (4) (product-related) sales services. This is in line with Rosenbloom's (2001) assertion that in order to satisfy the markets' needs "the products of producing and manufacturing firms must be made available to those markets" (p. 36).

6.3.3 Logistics Service Quality

Another important value-added activity of wholesalers is logistics. Mentzer, Gomes and Krapfel (1989) and Mentzer et al. (2001) argue that two elements exist in service delivery: marketing customer service (MCS) and physical distribution service (PDS). In this study MCS is partly incorporated in the service quality and product quality scales. Based on recent literature (e.g., Meuter, Ostrom, Roundtree and Bitner, 2000), which emphasizes the role of technology in logistics, we divide logistics service quality (LSQ) into (a) service technologies (ST quality), and (b) physical distribution service. Incorporating ST quality into the LSQ scale is frequently suggested by supply chain researchers. As argued by Mentzer and Bird (1997, p. 34), business-to-business logistic services are offered in a context in which people are replaced with "things" and the customer and provider are often physically separated. Concerning the ST based literature, there is some literature investigating the quality perceptions when using ST (e.g., Dabholkar, 1996; Meuter et al., 2000). Meuter et al.'s (2000) findings suggest that the following three dimensions result in satisfying incidents: (1) system reliability, (2) time benefit, and (3) easy to use. Basically, Dabholkar's (1996) attribute-based model of technology-based self service options includes these three dimensions. Concerning PDS, an extensive stream of research has dealt with this element (e.g., Mentzer et al., 1989; Mentzer et al. 2001). In general, this stream of research emphasizes components like order accuracy, timeliness and tangibles. Building on the previously mentioned streams of research, we incorporate six logistics service quality dimensions: (a) order reliability, (b) simplicity, (c) convenience, (d) accuracy, (e) timeliness, and (f) tangibles.

6.3.4 Information Quality

According to Mentzer et al. (2001) information quality refers to customers' perceptions of the information provided by the supplier's organization. Several researchers propose various information quality constructs (e.g., Innis and La Londe, 1994; Maltz and Kohli, 1996; Moenaert and Souder, 1996). Based on this stream of research and the interviews, as described in chapter 1, we propose the following dimensions of information quality: (1) comprehensiveness, (2) relevance, and (3) transparency. The scales for both comprehensiveness and relevance are derived from the literature (Innis and La Londe, 1994; Moenaert and Souder, 1996). The third subdimension of information quality, transparency, is derived from field interviews. These interviews indicate that transparency is an important component of

information quality in wholesaling.

6.3.5 Sample

As already mentioned, we develop a quality measure for the wholesaling industry. To generate data, we use the official records of the Dutch Chamber of Commerce's database to select potential customers of electrotechnical wholesalers. We sent 2921 questionnaires to these potential customers in the Netherlands. The customers are asked to rate the degree to which they are satisfied with the offerings of one of their wholesalers in 46 questions and to give the name of this supplier. These questions are measured on a seven-point scale, where 1 = "strongly disagree" and 7 = "strongly agree." Also, we add a question indicating their overall satisfaction with the wholesaler; this measure is used in Study 2. We measure satisfaction with one indicator, which represents an overall judgment (satisfaction with numerous transactions) of the wholesalers. We measure this indicator on a ten-point Likert scale, where 1 = "very dissatisfied" and 10 = "very satisfied." The mailing result in 490 responses, which is a response rate of 16.8%.

6.4 Results Study 1

Table 6.1 shows the descriptive statistics and correlations. First, the correlation between the components of each dimension of WholeSaleQual is moderate to high ($\geq .45$ for service quality, $\geq .43$ for product quality, $\geq .41$ for logistics service quality and $\geq .35$ for information quality) and significant. Second, the correlation between all subdimensions of WholeSaleQual is also moderate to high. This provides us with a first impression about the factor structure. To fully investigate the best fitting factor structure confirmatory factor analysis is applied.

By using confirmatory factor analysis, the researcher does not 'prove' the proposed model but only confirms that it is one of several possible models. Therefore, it is possible that a different model could fit the data more adequately. Here, we estimate two models: (1) an eighteen first-order factor model (operational level model), and (2) a four second-order factor model with eighteen first-order factors (hierarchical model). Then we compare the first model with the hierarchical one.

6.4.1 Operational Factor Structure

Consistent with the micro-level quality management literature, we incorporate all dimensions (subdimensions from our hierarchical factor model) as first-order factors. Our confirmatory factor analysis indicates the following fit statistics for the operational level model: $\chi^2 = 1186.34$, d.f. = 512, $p = .00$, RMSEA = .052; SRMR = .037; NNFI = .98; CFI = .99; IFI = .99. Although the χ^2 statistic is significant, other fit statistics suggest an excellent representation of the variance-covariance matrix to the hypothesized measurement model. The reliability coefficients and average variance extracted are acceptable (Appendix E).

	Mean	Sd	1a	1b	1c	1d	1e	2a	2b	2c	2d	3a	3b	3c	3d	3e	3f	4a	4b	4c	5	
1. Service Quality																						
1a. Reliability	5.51	1.03	-																			
1b. Responsiveness	5.74	1.01	.69**	-																		
1c. Assurance	5.86	.88	.61**	.69**	-																	
1d. Empathy	5.55	1.07	.48**	.66**	.65**	-																
1e. Tangibles	5.63	.89	.45**	.51**	.54**	.49**	-															
2. Product Quality																						
2a. Reliability	5.52	1.05	.41**	.42**	.36*	.30**	.39**	-														
2b. Customization	5.93	.74	.39**	.44**	.42**	.36**	.47**	.69**	-													
2c. Availability	5.28	1.09	.45**	.39**	.37**	.33**	.41**	.60**	.57**	-												
2d. Sales Services	4.98	1.40	.41**	.47**	.48**	.52**	.38**	.43**	.44**	.46**	-											
3. Logistics Quality																						
3a. Reliability	5.94	.83	.57**	.55**	.53**	.50**	.42**	.57**	.66**	.63**	.42**	-										
3b. Accuracy	5.67	.97	.46**	.47**	.42**	.45**	.44**	.50**	.55**	.56**	.28**	.72**	-									
3c. Simplicity	6.25	.84	.36**	.44**	.51**	.34**	.37**	.35**	.45**	.45**	.34**	.63**	.41**	-								
3d. Timeless	5.87	.94	.55**	.52**	.56**	.39**	.45**	.50**	.55**	.64**	.40**	.71**	.57**	.65**	-							
3e. Condition	5.83	.87	.43**	.47**	.45**	.39**	.47**	.51**	.56**	.42**	.30**	.66**	.62**	.49**	.52**	-						
3f. Tangibles	5.91	.86	.31**	.39**	.38**	.35**	.39**	.49**	.54**	.38**	.29**	.57**	.43**	.44**	.51**	.60**	-					
4. Information Quality																						
4a. Relevance	5.50	1.01	.42**	.49**	.45**	.38**	.48**	.57**	.60**	.55**	.46**	.55**	.41**	.48**	.55**	.45**	.51**	-				
4b. Comprehensiveness	5.18	1.17	.48**	.55**	.51**	.59**	.50**	.52**	.48**	.55**	.69**	.55**	.39**	.46**	.55**	.45**	.46**	.67**	-			
4c. Transparency	5.50	1.39	.43**	.43**	.43**	.42**	.32**	.40**	.40**	.51**	.39**	.49**	.35**	.46**	.49**	.36**	.38**	.60**	.52**	-		
5. Customer Satisfaction	7.93	.86	.44**	.47**	.38**	.36**	.28**	.29**	.38**	.33**	.26**	.47**	.35**	.33**	.43**	.31**	.26**	.44**	.39**	.35**	-	

* p < .05; ** p < .01.

Table 6.1: Descriptive Statistics and Correlations

6.4.2 Second-order Factor Model

The fit statistics for the second-order factor model show the following values: $\chi^2 = 2227.39$, d.f. = 641, $p = .00$; RMSEA = .072; SRMR = .065; NNFI = .97; CFI = .97; IFI = .97. The chi-square value is significant. Other goodness-of-fit measures, however, indicate a reasonable overall fit of this hierarchical model of quality to the data.

Summary. Our results indicate, based on the fit statistics, that an operational quality model fits the covariance matrix significantly better than the hierarchical model. For example, RMSEA and SRMR are significantly smaller in the case of an operational factor structure. Also, NNFI, CFI and IFI statistics are higher for the operational factor model, indicating a better relative fit. This suggests that despite the high correlations (see table 6.1), confirmatory factor analysis could discriminate between the subdimensions. These findings do support hypothesis 1 and demonstrate that an operational quality model is superior in assessing customer perceptions of quality in wholesale.

6.5 WholeSaleQual and Performance (Study 2)

In the process of making service-delivery decisions, different members, who focus on different attributes based on their orientation, may influence the final decision making. For example, the product manager might focus on product-related aspects, such as product reliability, whereas the logistics manager is more concerned with on-time delivery and the ordering process. Hence, allocation of resources to improve performance may become very complex. Management is frequently asking questions as: which operational variables are essential or relatively more important to ensure and improve market performance? and how can we formally investigate this? In this study, we propose a method, operational level analysis combined with partial least squares regression, that may facilitate the decision-making process in

business markets, such as wholesaling. This method may help managers faced with the problem of how to trade off competing quality improvement initiatives. Hence, the aim is twofold: (1) to show the relevance of this theoretical model, and (2) to reveal the strength of partial least squares regression in dealing with marketing models showing high levels of multicollinearity.

Concrete, this method enables us to relate the operational quality model to customer satisfaction. Concerning our theoretical relationships, ample research suggests the importance of these links. For example, the marketing perspective proposes that quality perceptions, in the aggregate, directly lead to customer satisfaction (cf., Anderson and Sullivan, 1993). However, we are unaware of a comprehensive disaggregated model that relates operational quality dimensions to customer satisfaction in a wholesaling context. Hence, we hypothesize that

hypothesis 2 WholeSaleQual dimensions have a positive effect on customer satisfaction

6.5.1 Partial Least Squares Regression

A dark side of quality data is the occurrence of severely skewed frequency distribution and high multicollinearity (Fornell, 1995). Several methods have been proposed in the statistical literature to deal with this problem, such as principle components regression (Massy, 1965), Sliced Inverse Regression (Li, 1990) and partial least squares regression (Martens and Naes, 1989). However, previous research suggests the superiority of PLSR on both principle components regression (Frank and Friedman, 1993) and sliced inverse regression (Naik and Tsai, 2000). Therefore, to investigate hypothesis 2, we utilize univariate partial least squares regression (PLSR).²

PLSR is a linear regression method based on partial least squares (Wold, 1966). PLSR is an algorithm that models the relationship between an \mathbf{Y} variable or a set of \mathbf{Y} variables and independent variables.³ Next, a brief summary of the PLSR algorithm will be given; a more detailed treatment is provided by Martens and Naes (1989) and Martens and Martens (2001).

Partial Least Squares Regression

In general, the algorithm consists of three steps (see for detailed discussion, Höskuldsson, 2003; Martens and Martens, 2001): (1) computation of the PLS com-

²As mentioned before, a popular method to investigate the previous proposition is to use principle component regression. However, PLSR is found to have better properties (see for example, Frank and Friedman, 1993). A problem inherent in using principle component regression, as pointed out by Jolliffe (1982), is the risk that small structures in \mathbf{X} , which may well explain \mathbf{Y} , disappear in the PC modeling of \mathbf{X} .

³Note that although some may believe that the partial least squares algorithm originally developed by Wold (1973, 1982), also known as partial least squares path modeling, and PLSR (Wold, Martens and Wold, 1983; Martens and Naes, 1989) are equivalent, this is not the case (See Martens (2001) discussing this issue).

ponents [\mathbf{t}_a ($a = 1, \dots, A$)], (2) estimation of a linear regression of \mathbf{Y} on the retained principle components (PCs), and (3) jack-knife validation, or alternatively other resampling methods, such as bootstrapping, of the parameters in the final model.

In the first step, the weights are found as the eigenvector of the matrix $\mathbf{X}_{a-1}^T \mathbf{Y} \mathbf{Y}^T \mathbf{X}_{a-1}$. Then the linear PLSR model estimates a few variables (latent variables) called X-scores, denoted by \mathbf{T} [\mathbf{t}_a , $a = 1, 2, \dots, A$]. The X-scores are orthogonal and estimated as linear combinations of the original X-variables with the weight coefficients \mathbf{W} (\mathbf{w}_a , $a = 1, 2, \dots, A$).

Once the proper number of PCs to retain is chosen, the second step concerns the estimation of \mathbf{Y} on the retained PLSR components. The third step seeks to validate the coefficients. Since the statistical theory cannot be used, because the vector of regression coefficients is a nonlinear function of \mathbf{Y} , to ascertain statistical significance of the parameters, resampling methods, such as jack-knifing, are frequently used (see Martens and Martens, 2001).

The Prediction Model

After estimating the model, a prediction model can be determined. The common way to estimate a prediction model is by projecting the new \mathbf{X} values onto the model in order to calculate new scores and then using these scores to predict new samples (Hoy, Steen and Martens, 1998)

$$\mathbf{y}_{ij,pred} = \mathbf{y}_j + \mathbf{t}_{i,pred} \mathbf{q}_j^T \quad (6.1)$$

where i is the sample number, j is the \mathbf{y} -variable number, $\mathbf{t}_{i,pred}$ is the new scores and \mathbf{q}_j is the \mathbf{y} -loadings from the likelihood.

Model Complexity

PLSR, which is often used with numerous and correlated \mathbf{X} -variables, is rather sensitive and substantial risk for over-fitting exists. Therefore, it becomes essential to determine the correct complexity of the model by establishing the predictive significance of each PC. The standard practice to determine model complexity in this stream of research is to calculate the prediction error by means of cross-validation. This presents a practical and reliable method to check the predictive validity of the obtained model.⁴ The root mean squares errors of prediction (RMSEP) is employed for comparison among models, which is given by

$$\mathbf{RMSEP} = \sqrt{\frac{1}{N} \sum_{i=1}^n (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2} \quad (6.2)$$

where \mathbf{y} represents the actual value and $\hat{\mathbf{y}}$ is the value of the predicted variable.

⁴Note that cross validation is, in the absence of an independent validation set, used to establish model validation.

6.6 Results

In this study, we mean-center both the \mathbf{Y} and \mathbf{X} variables. We use the *UnscramblerTM*, version 9.1, to analyze the models. Next, we present our results in the following sequence. First, we relate the dimensions of WholeSaleQual to customer satisfaction, using PLSR. Second, after we investigate the PLSR model, we estimate an ordinary least squares (OLS) regression in order to examine the degree to which this method is relatively superior or inferior in estimating models of our class of data.

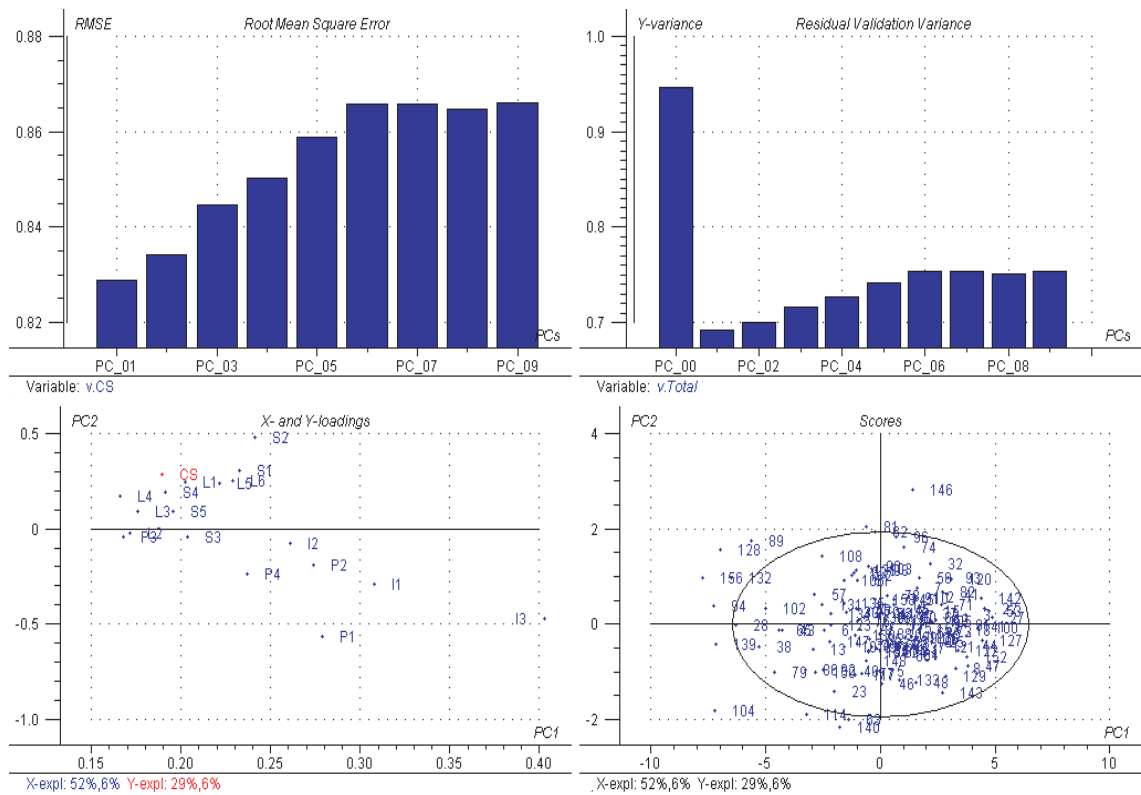
6.6.1 Model Outcomes

PLS regression is run with eighteen wholesale quality dimensions as \mathbf{X} -matrix and customers' overall satisfaction as \mathbf{Y} -matrix. Figure 6.1 summarizes the results of our analysis in an accessible graphical manner. The first step is to determine the correct complexity of the model. The upper left plot of figure 6.1 indicates the root mean squares error of prediction (RMSEP). RMSEP shows that one PC may be the optimal number of PCs. Furthermore, the upper right plot, the residual validation variance plot, also indicates that one PC is correct, because it reaches a minimum after PC_00, which represents the average point in the data set. Actually, one PC explains 52% of the variance in \mathbf{X} . This PC explains 29% of the variation in \mathbf{Y} . Since PLSR is rather sensitive to outliers we also compute the Hotelling T^2 Ellipse. The 95 percent confidence ellipse shown in the lower right plot of figure 6.1 is based on Hotelling T^2 statistic. Observations well outside the Hotelling Ellipse are outliers. In our case the number of outliers is limited. This leads us to believe that they may not have a (serious) effect on the obtained results.

The PLS-regression coefficients reveal the strength of the relationship between WholeSaleQual dimensions and overall customer satisfaction. Figure 6.2 shows the estimated effects and their reliability ranges. The error bars in this figure show estimates of the reliability range of \hat{b} , expressed as $\hat{b} \pm 2\hat{s}(\hat{b})$, where $\hat{s}(\hat{b})$ is estimated by cross-validation of the model parameters (jack-knifing) (see for a discussion, Martens and Martens, 2001). The regression outcomes show small uncertainty limits. The sign of all the variables is positive and the effect is clearly non-zero. All coefficients have their jack-knife distributions well above zero and thus can be considered statistically significant. So, hypothesis 2 is confirmed. The figure shows that the clearest and strongest predictors for customer satisfaction are dimensions of information quality (information relevance, comprehensiveness and transparency) and service responsiveness (S_1) and reliability (S_2).

In short, we obtain the following equation

$$\begin{aligned} \text{Customer Satisfaction} = & .052\mathbf{S}_1 + .056\mathbf{S}_2 + .032\mathbf{S}_3 + .037\mathbf{S}_4 + .037\mathbf{S}_5 + .040\mathbf{P}_1 + \\ & .046\mathbf{P}_2 + .034\mathbf{P}_3 + .035\mathbf{P}_4 + .044\mathbf{L}_1 + .030\mathbf{L}_2 + .031\mathbf{L}_3 + \\ & .035\mathbf{L}_4 + .046\mathbf{L}_5 + .048\mathbf{L}_6 + .054\mathbf{I}_1 + .055\mathbf{I}_2 + .069\mathbf{I}_3 \end{aligned} \quad (6.3)$$



note: CS is customer satisfaction, S1 is service responsiveness, S2 is service reliability, S3 is service tangibles, S4 is assurance, S5 is empathy, P1 is product-related sales services, P2 is product availability, P3 is customization, P4 is product reliability, L1 is timeless, L2 is logistics tangibles, L3 is condition, L4 is order simplicity, L5 is accuracy, L6 is order reliability, I1 is information relevance, I2 is information comprehensiveness and I3 is information transparency.

Figure 6.1: The PLS-graphical outcomes

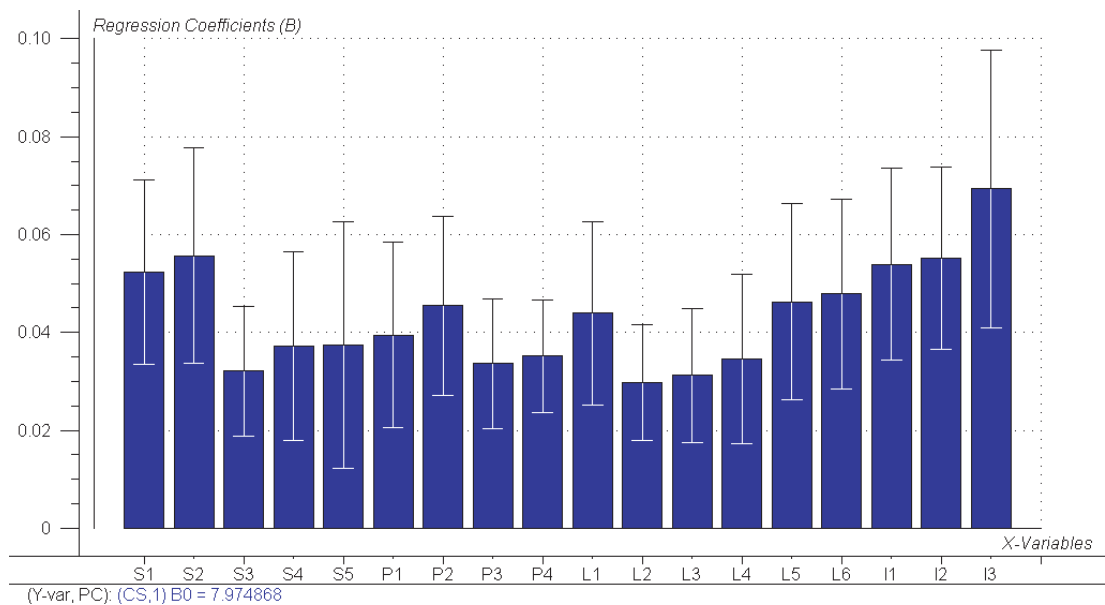
6.6.2 The Prediction Results

After we have estimated the model using both the \mathbf{X} and \mathbf{Y} variables, we now estimate a model, based on projection, that only contains \mathbf{X} variables (the prediction model). We estimate the model for the prediction of customer satisfaction.

Figure 6.3 graphically displays the outcomes. Generally, no wrong predictions are given; all predictions are less than one and a half and higher than minus two and a half. The variation is sometimes high, which indicates that some of the predictions are not well. In general, the predictions are relatively well. This provides further strength for the estimated model and established relationships.

6.6.3 PLSR vs. Ordinary Least Squares Regression

Quality researchers, despite the risk of high multicollinearity between \mathbf{X} -variables, largely investigate the relationship between independent and dependent variables using ordinary least squares (OLS). To investigate the degree to which this approach is justified in the case of highly correlated operational variables, we estimate the model



note: S1 is service responsiveness, S2 is service reliability, S3 is service tangibles, S4 is assurance, S5 is empathy, P1 is product-related sales services, P2 is product availability, P3 is customization, P4 is product reliability, L1 is timeless, L2 is logistics tangibles, L3 is condition, L4 is order simplicity, L5 is accuracy, L6 is order reliability, I1 is information relevance, I2 is information comprehensiveness and I3 is information transparency.

Figure 6.2: 95% Jack-Knife Confidence Intervals of the PLS Regression Coefficients in the Likelihood Model

by means of OLS regression and compare the results with the previously estimated PLSR outcomes.

Figure 6.4 shows the regression outcomes of the WholeSaleQual-customer satisfaction relationship. Unlike PLS regression parameters, these (OLS) parameters are all, see the p -values plot (lower plot), statistically nonsignificant; the t -values are all less than 1.8.

Confronting the previously mentioned results with that of PLSR, we can see, from a pragmatical view, that OLS regression frequently performs bad relative to PLSR. This result is also widely reported in the statistical literature (e.g., Garthwaite, 1994; Wold, Sjöström and Eriksson, 2001). The analyses suggest that PLSR reduces the ‘lack of selectivity’ problem (that no single X-variable is sufficient to predict \mathbf{Y}) even in the case of collinear and noisy independent variables. In short, the results suggest the strength of PLSR as a method to predict dependent variable(s) in the case of high multicollinearity between variables.

6.7 Contributions

In this paper, we provide an approach and method for translating customer feedback into managerial actions for improving market performance. This analysis enables managers in wholesaling to recognize the quality attributes that need to be improved to stimulate customer satisfaction. Next, we cite some contributions of

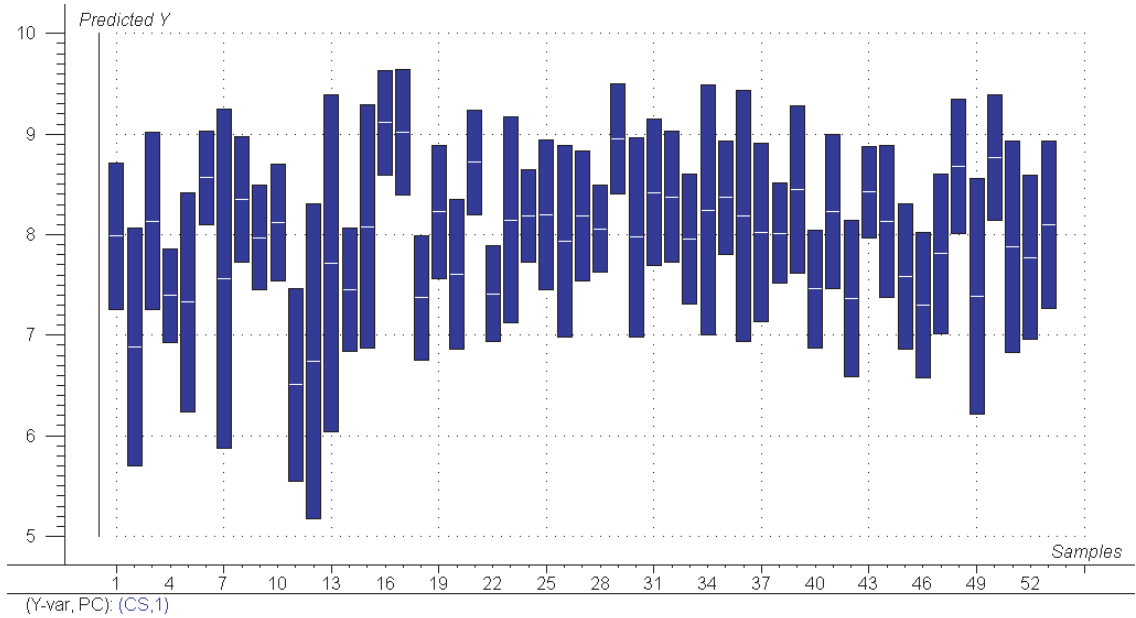


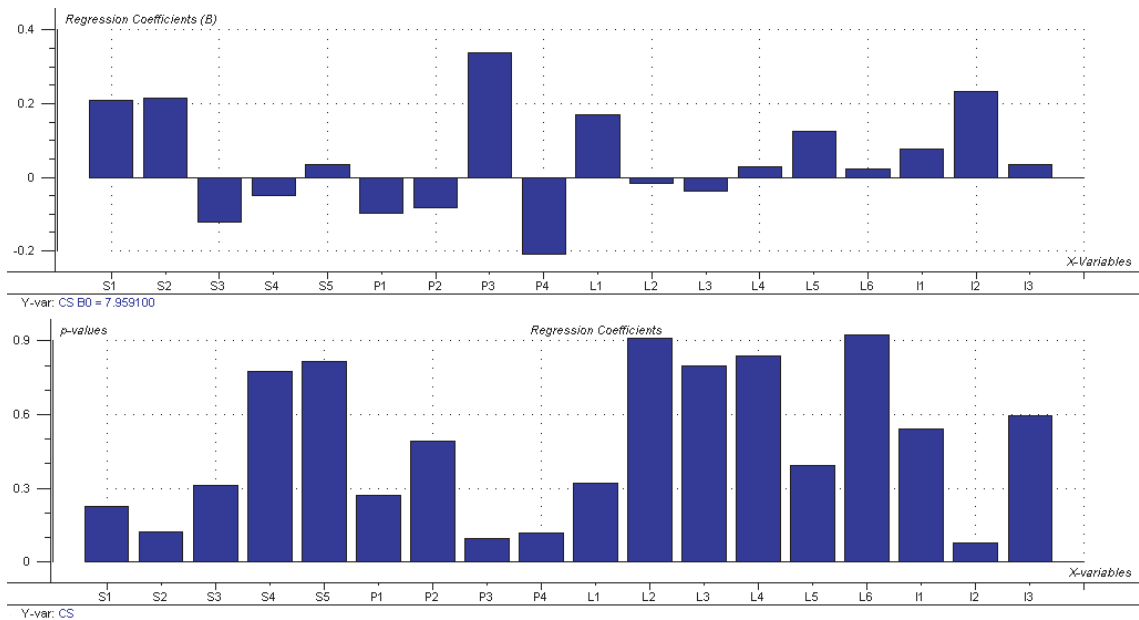
Figure 6.3: The Prediction Model

this article.

The first contribution is the development of the WholeSaleQual construct. Although many quality constructs exist, little research has been conducted to develop a broad quality construct by incorporating several quality dimensions for wholesaling. The proposed model is especially valuable, since the customers of wholesalers receive services, product, information and form quality perceptions about logistics services. As far as we know, this is the first attempt to develop a comprehensive quality model for wholesaling.

A second contribution is the investigation of two plausible models of WholeSaleQual, a hierarchical and a nonhierarchical quality model. Since no comprehensive quality construct exists for wholesaling, this step is necessary. Furthermore, it provides the marketing researcher and practitioner with valuable information: on which criteria (and level) do customers make decisions? Based on our findings, we recommend the nonhierarchical (operational) quality model.

Good marketing data is scarce and frequently suffers from (high) collinearity, and therefore cannot be analyzed appropriately with most regression methods. A consequence of this is that marketing researchers and scientists only model those variables that they think are most important, and thus eliminate other (possible useful) variables. A third contribution is our application of a method of analysis that provides good estimates, even in the presence of a rather small sample size and high multicollinearity. This method is originally introduced in econometrics and further developed in chemometrics. However, despite its possible advantages, this method is largely ignored. With PLSR one can investigate the impact of all variables



note: CS is customer satisfaction, S1 is service responsiveness, S2 is service reliability, S3 is service tangibles, S4 is assurance, S5 is empathy, P1 is product-related sales services, P2 is product availability, P3 is customization, P4 is product reliability, L1 is timeless, L2 is logistics tangibles, L3 is condition, L4 is order simplicity, L5 is accuracy, L6 is order reliability, I1 is information relevance, I2 is information comprehensiveness and I3 is information transparency.

Figure 6.4: OLS Regression Results

simultaneously. For example, Parasuraman et al.'s (1985) original SERVQUAL model could be estimated without worrying too much about (multi)collinearity. By applying this pragmatic method a manager can answer questions as: should the firm increase service responsiveness, improve product attributes, invest in logistics or none of the above? In short, this method enables management to identify specific customer needs and to efficiently allocate resources to (a) offer better products and services, (b) redesign products and services, and (c) introduce more desired products and services in order to fully maximize perceived quality.

In this study, we initially use confirmatory factor analysis (CFA) to refine the constructs under study. Then we estimate a univariate partial least squares regression model. The combination of these methods simplified the analysis and thus the interpretations of the obtained results. It provides us with a clear sense of the product, information, and service attributes that customers desire most. Furthermore, the PLSR outcomes supply in-depth information about the importance of the attributes to market performance. It reveals some relevant information for service improvements, such as the importance of information quality in enhancing customer satisfaction. Also, some quality attributes are less influential, such as service empathy, product-related sales services and product quality. This kind of information is essential to guide a company's market strategy.

A fifth contribution is our explicit link between operational level analysis and PLSR as a method to implement this approach. Actually, former research using an operational level modeling approach tends to use one of four methods: (1) correlation

analysis, (2) multiple regression analysis, (3) covariance analysis, and/or (4) data envelopment analysis. These four methods provide only unbiased estimates when some assumptions are fulfilled. First, applying these four methods in conducting operational level modeling, especially when operational variables tend to be numerous, requires a rather high sample size. Second, because operational variables are in general highly correlated, multiple regression and covariance analysis give biased estimates. Third, correlational analysis does not indicate causality. Fourth, data envelopment analysis requires very specific data and it does not tell which operational variables will lead to some improvements. PLSR, on the contrary, does not require high sample size and uncorrelated independent variables. Furthermore, it provides an indication of causality and generates specific outcomes that may facilitate the decision-making process.

6.8 Limitations

As with every study, this research has limitations. The first limitation concerns our proposed analytical method. A major drawback of the PLSR method is its vague statistical behavior. This makes it difficult to perform usual inferential tasks related to modeling, such as assessing uncertainty in coefficient estimates. Therefore, a major problem of PLSR is that we cannot make the quantitative probabilistic statement like “95% confidence.” However, PLSR is generally used when many independent variables and high (multi)collinearity among these variables exist. In this case, the traditional approach to selecting variables, based on significant testing, has some basic defects (see for a discussion, Höskuldsson, 2003). Therefore, we think that Martens and Martens’ (2000) approach, based on jack-knifing, is appropriate to detect the parameters uncertainty in our present case.

A second limitation is related to our developed WholeSaleQual construct. Although we carefully integrate different constructs, we find some high cross-correlations. For example, some subdimensions of logistics service quality are also related to some dimensions of WholeSaleQual (i.e., service quality and product quality). Future research has to deal with this issue and ought to develop measures and to seek for methods to improve the convergence and discriminant validity of the measures.