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Market-based capabilities, perceived quality and firm performance

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Chapter 3

A Detailed Investigation of the Market-Based Capabilities-Firm Performance Link: A Multivariate Partial Least Squares Regression Analysis

Abstract This study seeks to investigate the relationship between market-based capabilities and firm performance in the Dutch wholesale industry. It extends previous work by providing a more detailed investigation of the relationships. To predict the proposed links multivariate partial least squares regression is applied. The findings suggest that superiority of a wholesale company in terms of five performance measures (sales growth, profit growth, overall profitability, labor profitability and cash flows) can be explained by a set of eight market-based capabilities (customer-driven, competitor-driven, customer-linking, supplier-linking, information-technology, logistics, human-related and people capabilities). These results provide further support for the market-based capabilities framework, as proposed and developed in the previous chapter. Furthermore, partial least squares regression proves to be a valuable method in analyzing the relationships, whereas ordinary least squares regression largely fails to present relevant and valuable management information. Our approach, analytical method and findings have some implications for management in the wholesale industry.

3.1 Introduction

In the previous chapter, a new instrument is developed, called the market-based business capabilities model, that links the resource-based view to the marketing-based view. In this study, four types of company's rent producing (market-based) resources are derived: (1) market-driven capabilities, (2) relationship-driven capabilities, (3) supply-chain capabilities, and (4) human-resource capabilities. Relating these market-based capabilities simultaneously to firm performance, no support is found for the hypothesis that marketing-related capabilities (marketing-driven and relationship-driven capabilities) significantly predict firm performance. These two variables, in isolation, however, have a strong effect on firm performance. Although this study provides some new insights, the previously mentioned results limit its managerial relevance, especially for marketing managers. To overcome this, we extend our study by relating the components of the four market-based capabilities, which are in general highly collinear, to (several indicators of) a firm's financial performance.

Concerning the links in our theoretical framework, ample literature on both

marketing and management operations provides impressive support for the presence of significant relationships. There is, however, little evidence for the effectiveness of developing both outside-in and inside-out capabilities simultaneously. Therefore, the study's general proposition is that a firm performance, in terms of five qualitative financial performance measures (sales growth, profit growth, overall profitability, labor profitability and cash flows), can be explained by a set of eight market-based capabilities (customer-driven, competitor-driven, customer-linking, supplier-linking, information-technology, logistics, human-related and people capabilities). In doing so, we utilize a rather sophisticated method in investigating these links: multivariate partial least squares regression.¹

Multivariate partial least squares regression facilitates the identification of the effect of key variables on several dependent variables. This method can handle many noisy, collinear and even incomplete variables in both \mathbf{X} and \mathbf{Y} (Wold, Sjöström and Eriksson, 2001). Utilizing partial least squares regression has many advantages (see for a detailed discussion, Martens and Martens (2001)). First, partial least squares regression aims to improve the predictive efficiency of the regression model by finding score vectors for \mathbf{X} that are more likely to correlate to the columns of \mathbf{Y} . Second, models with highly correlated independent variables can be treated well with this method. Third, multivariate PLS decomposes both \mathbf{X} - and \mathbf{Y} -variables, which makes it possible to use a large number of independent and dependent variables. Fourth, partial least squares regression de-emphasizes the less important variables by giving them a small loading compared to important variables. Fifth, this algorithm is very useful in the case of many explanatory variables and comparatively little sample data (Garthwaite, 1994; Höskuldsson, 1988). Sixth, it is suggested that multivariate PLSR is particularly useful when the \mathbf{Y} variables are known to be strongly intercorrelated with each other; actually, the intercorrelation structure is used by multivariate PLSR as a stabilizing factor (Martens and Naes, 1989).

This chapter is organized as follows. In the next section, we briefly review some literature suggesting the relationship between several market-based dimensions and firm performance. We then describe very briefly the theory behind PLSR, especially multivariate PLSR. Multivariate PLS regression results are then presented and further discussed. Finally, we conclude by discussing the implications of the obtained findings, the limitations of the study and identify future research directions.

3.2 Conceptual Framework

Looking broadly to the (strategic) marketing literature, it appears that during the past years there has been some debate on the question: is marketing a set of values (culture) or a capability? Although this is an ongoing debate, it has discouraged marketing researchers from fully integrating the resource-based view

¹Previous research, in general, uses ordinary least squares regression or structural equation modeling in relating market-based variables to firm performance. These methods, however, are not appropriate when high collinearity between independent variables is present. Furthermore, these methods cannot estimate a model containing highly collinear and noisy dependent or latent variables (\mathbf{Y}) and independent variables (\mathbf{X}).

into marketing. However, recently, some literature, although highly conceptual (e.g., Srivastava et al., 2001) has emerged discussing the advantage of relating the resource-based view to marketing, especially to the concept of market orientation. Their main thesis is that an integrative approach is more likely to provide a stronger base for (the development of) competitive advantage. An additional reason to investigate an integrative concept of marketing relates to the mixed results of recent empirical studies relating market orientation (as a set of values) to business performance (e.g. Moorman and Rust, 1999; Noble, Sinha and Kumar, 2002). Furthermore, there is some literature indicating that a market orientation is not always the only viable strategic orientation (e.g., Heskett et al., 1994; Noble et al., 2002; Treacy and Wiersema, 1995).

In chapter 2, we develop and validate a model which links the marketing-based view to the resource-based view of competitive advantage. Chapter 3 aims to further investigate the basic question asked by marketing and resource-based researchers: do market-based capabilities account for variation in firm performance? As mentioned before, we extend the previous chapter by taking a rather disaggregated approach by relating the dimensions of the four market-based capabilities (customer-driven, competitor-driven, customer-linking, supplier-linking, information-technology, logistics, human-related and people capabilities) to several indicators of firm performance (sales growth, profit growth, overall profitability, labor profitability, and cash flows). This operational-level analysis is a preferable approach if the purpose of the study is to identify necessary organizational changes (e.g., Chase and Bowen, 1991; Rust, Zahorik and Keiningham, 1995; Soteriou and Chase, 1998, 2000; Soteriou and Zenios, 1999). Basically, models of sustainable competitive advantage (e.g., Day and Wensley, 1988; Bharadwaj, Varadarajan and Fahy, 1993; Hunt and Morgan, 1995; Srivastava et al., 2001) implicitly recognize this level as the appropriate level of analysis. These models sum a large number of strategic and operational variables, which are often highly related, as having an impact on a firm's (positional) advantage. In short, this analysis helps management in making trade-offs (and allocating resources) in order to create a unique and valuable position in the market place.

Concerning the links in our theoretical framework, ample literature on both marketing and management operations provides impressive support for the presence of significant relationships. Concerning customer-driven and competitor-driven capabilities, Narver and Slater (1990) among others, suggest that firms excel when they understand and respond to their customers and competitors more effectively than their rivals do. These and subsequent studies in general find support for their proposition (e.g., Cano, Carrillat and Jaramillo, 2004; Kirca, Jayachandran and Bearden, 2005).

The value of relationship-driven capabilities to firm performance is frequently studied (e.g., Kalwani and Narayandas, 1995; Uzzi, 1996; Uzzi and Lancaster, 2003). For example, Rosenzweig et al. (2003) argue that highly integrated supply chains have the potential to lower the net costs of conducting business and the total delivered costs to customers (p. 439). According to these researchers, this is done by: (1) working closely with firms over time, so that wholesalers have more opportunities for correcting any transaction inequities, (2) sharing interfirm information

that reduces information asymmetry, and (3) using noncontractual, self-enforcing safeguards which are less costly than more traditional legal contracts. Empirically, Rosenzweig et al. (2003) demonstrate that high relationship-driven capabilities (i.e., interorganizational information sharing and cooperation) directly influence superior product quality, delivery reliability, process flexibility, and cost leadership. Kalwani and Narayandas (1995) suggest that manufacturers who adopt a relational view are more able to retain and improve their profitability than manufacturers who adopt a transactional approach. Frohlich and Westbrook (2001) find evidence that the widest degree of arc of integration with both suppliers and customer has the strongest association with performance improvement.

Concerning supply-chain capability, its relationship to business performance is frequently suggested by operations management scientists. The impact of information technology capabilities (ITC) on business performance is frequently studied in various settings (for a review of the literature, see Brynjolfsson and Hitt, 2000; Bharadwaj, 2000). The evidence from these studies seems to be mixed. However, ample research indicates a positive contribution of ITC to firm performance (Bharadwaj, Bharadwaj and Konsynski, 1999; Mata, Fuerst and Barney, 1995). Concerning logistics capabilities, several studies suggest that a distinctive logistics capability is a source of sustainable competitive advantage and superior performance (Lynch, Keller and Ozment, 2000; Olavarrieta and Ellinger, 1997).

The impact of human resource management on firm performance is frequently suggested in the literature (e.g., Huselid 1995; Huselid et al. 1997; Richard and Johnson 2001). Although no consensus exists concerning the sign and effect, ample research suggests a direct and positive relationship between human resource management and firm performance (see for a review, Wright and Boswell, 2002). The relationship between people capabilities and firm performance is generally proposed, although this stream of research largely suggests a mediating role for customer perceptions, i.e., service quality and trust (Hartline, Maxham and McKee, 2000; Roth and Jackson, 1995). For example, Roth and Jackson (1995) argue that “individual knowledge affects service quality by diminishing organizational uncertainty and improving the firm’s ability to adapt to new conditions” (p. 1724). These researchers confirm the proposition that people capabilities affect service quality and business performance.

In summary, we relate the components of the four market-based capabilities to several indicators of firm performance and propose that these components, taken simultaneously, have an effect on each indicator of firm performance.

3.3 Methods of Analysis

In this study, we take an operational level modeling approach by relating a set of eight market-based capabilities to several performance measures. Ordinary least squares regression (OLS) is a widely used method to establish these kinds of relationships. This algorithm predicts well under certain assumptions. However, in operational level modeling we frequently encounter many noisy and collinear

independent variables, which are used to predict a dependent variable. In this case OLS may not predict well, because this method only works well as long as the number of \mathbf{X} variables is fairly small and fairly uncorrelated, i.e. \mathbf{X} has full rank (Greene, 1997). If this is not the case (\mathbf{X} has no full rank) the inverse of \mathbf{X} does not exist. In response to these problems, several methods have been proposed to deal with this problem, e.g., principal components regression (PCR) (Jolliffe, 1986), partial least squares regression (PLSR) (Wold, Martens and Wold, 1983), Sliced Inverse Regression (SIR) (Duan and Li, 1991; Li), ridge regression (Hoerl and Kennard, 1970) and equity estimators (Krishnamurthi and Rangaswamy, 1987). Naik and Tsai (2000), in a recent study, show that PLSR is more efficient and provides more accurate estimates than SIR when the link function is nonlinear.² Of these methods only PLSR, which is originally introduced in econometrics and further developed in the field of chemometrics, uses multiple dependent variables (\mathbf{Y}) and handles small sample sizes and high collinearity well. PLSR aims to improve the predictive efficiency of the regression model by finding score vectors for \mathbf{X} that are more likely to correlate to the columns of \mathbf{Y} . In short, this algorithm has many advantages when dealing with collinear data.

3.3.1 Partial Least Squares Regression

In the literature, PLSR is divided into: (1) univariate PLSR, often denoted as PLS1, and (2) multivariate PLSR, generally referred to as PLS2. To understand PLS2 it is necessary to first describe the more simple PLS1 algorithm.

PLS1

Assume that we have N observations with K X-variables denoted by x_k ($k = 1, 2, \dots, K$) and an y-variable. In general, PLSR modeling is based on two steps (Martens and Martens, 2001). First, the K input variables are compressed in \mathbf{X} to derive latent variables $\mathbf{T} = [\mathbf{t}_a, a = 1, 2, \dots, A]$

$$\mathbf{T} = \mathbf{W}(\mathbf{X}) \tag{3.1}$$

where $\mathbf{W}(\cdot)$ represents a linear function; each score vector \mathbf{t}_a is defined as a linear combination of the \mathbf{X} variables. The PLS components are considered to be orthogonal. Furthermore, function $\mathbf{W}(\mathbf{X})$ is defined so that the first few PCs are as \mathbf{Y} -relevant as possible. Step two models both \mathbf{X} and \mathbf{Y} in terms of \mathbf{T}

$$\mathbf{X} = \mathbf{TP}^T + \mathbf{E} \tag{3.2}$$

$$\mathbf{Y} = \mathbf{TQ}^T + \mathbf{F} \tag{3.3}$$

²In general, PLSR proves to be a powerful tool for data analysis when two blocks (\mathbf{X} and \mathbf{Y} block) are related but the exact form of that relationship is not necessarily known.

where \mathbf{P} is a matrix of PLS \mathbf{X} loadings, \mathbf{Q} is a matrix of PLS \mathbf{Y} weights and both \mathbf{E} and \mathbf{F} represent noise. The loadings (\mathbf{P} and \mathbf{Q}) are determined by least squares fit

$$\mathbf{P}^T = (\mathbf{T}^T \mathbf{T})^{-1} \mathbf{T}^T \mathbf{X} \quad (3.4)$$

$$\mathbf{Q}^T = (\mathbf{T}^T \mathbf{T})^{-1} \mathbf{T}^T \mathbf{Y} \quad (3.5)$$

Finally, the obtained model may be expressed as a linear regression model

$$\mathbf{Y} = \beta \mathbf{X} + \mathbf{F} \quad (3.6)$$

where \mathbf{F} represents the measurement error. For a model with A PCs, the matrix of regression coefficients (β) is defined as

$$\beta = \mathbf{W}(\mathbf{P}^T \mathbf{W})^{-1} \mathbf{Q}^T \quad (3.7)$$

As can be seen, the coefficients β are estimated as a function of \mathbf{W} , as well as a function of \mathbf{X} and \mathbf{Y} loadings \mathbf{P}^T and \mathbf{Q}^T , respectively.

PLS2

Previously, we described the univariate case. In the multivariate case, the algorithm is slightly different and more complex (see for a detailed discussion, Garthwaite, 1994; Höskuldsson, 1988; Wold, Sjöström and Eriksson, 2001). In contrast to PLS1, PLS2 makes a decomposition of \mathbf{Y} . Assume that we have N observations with K X-variables denoted by x_k ($k = 1, 2, \dots, K$) and J Y-variables, y_j ($j = 1, 2, \dots, J$). Hence, we have two matrices \mathbf{X} and \mathbf{Y} of dimension $(N \times K)$ and $(N \times J)$, respectively. As before, the first step is to find a few variables, called X-scores and denoted by \mathbf{T}_a ($a = 1, 2, \dots, A$). These X-scores are orthogonal and are estimated as linear combinations of \mathbf{X} , with the coefficients \mathbf{W}^*_a ($a = 1, 2, \dots, A$)

$$\mathbf{T} = \mathbf{X} \mathbf{W}^* \quad (3.8)$$

Similar to PLS1, we form a model for \mathbf{X} , where the \mathbf{t} 's are good summaries of \mathbf{X} and the X-residuals \mathbf{E} are small. This may be expressed as

$$\mathbf{X} = \mathbf{T} \mathbf{P}^T + \mathbf{E} \quad (3.9)$$

Then, unlike PLS1, we form a similar model for \mathbf{Y} . In this case, the corresponding Y-scores, denoted by \mathbf{U}_a are multiplied by \mathbf{Q} , which represent good summaries of \mathbf{Y} , so that the noise (\mathbf{F}) is small

$$\mathbf{Y} = \mathbf{U}\mathbf{Q}^T + \mathbf{F} \quad (3.10)$$

A second property is that \mathbf{T} serves as a predictor of \mathbf{Y}

$$\mathbf{Y} = \mathbf{T}\mathbf{Q}^T + \mathbf{G} \quad (3.11)$$

where \mathbf{G} summarizes the deviation between the observed and modeled responses. Integrating equation (3.8) into (3.11) we obtain a model that may be expressed as a linear regression model

$$\mathbf{Y} = \mathbf{W}^*\mathbf{Q}^T\mathbf{X} + \mathbf{G} = \beta\mathbf{X} + \mathbf{G} \quad (3.12)$$

Assuming an optimal model complexity, where the residuals are relatively small, the regression coefficient β , may be written as

$$\beta = \mathbf{W}^*\mathbf{Q}^T \quad (3.13)$$

For PLSR, matrix \mathbf{W}^* in equation (3.13) may be written as

$$\mathbf{W}^* = \mathbf{W}(\mathbf{P}^T\mathbf{W})^{-1} \quad (3.14)$$

In summary, the expression for the regression coefficient β is the same in PLS2 as in the PLS1 algorithm

$$\beta = \mathbf{W}(\mathbf{P}^T\mathbf{W})^{-1}\mathbf{Q}^T \quad (3.15)$$

3.3.2 Uncertainty Limits

In recent years, considerable effort has been invested in calculating confidence intervals for the regression coefficients and predictions for PLSR (e.g., Denham, 1997; Faber and Kowalski, 1997; Serneels, Lemberge and Ven Espen, 2004). However, this stream of research is still in its infancy and evidence is needed to fully assess the utility of the proposed methodologies. Recently, a rather pragmatical method has been introduced by Martens and Martens (2000) to calculate uncertainty limits

of the PLSR parameters. Since the PLSR parameters are linear combinations of the data and hence might be closely normally distributed, they propose to use the variation in the parameters of the submodels, which is obtained during cross validation, to derive standard deviations. This is then followed by applying the t -distribution to derive confidence intervals. The estimates of the reliability range of the regression coefficient vector (β) may be expressed as $\beta \pm 2 s(\beta)$. The standard uncertainty, $s(\beta)$, is obtained by summarizing the partial perturbations between the full model and the cross-validation segments, $\beta - \beta_m$ over the M segments (see for a detailed discussion, Martens and Martens, 2001). In PLS2, the regression coefficient vector is shown for each Y-variable, with the corresponding jack-knife estimate of reliability ranges $\beta_A \pm 2 s(\beta_A)$. Before proceeding, a cautionary remark must be made. Martens and Martens' (2001) derived reliability estimates are conditioned only on the available data, without any distributional assumptions. Hence, the jack-knife t -test might only be used as a rough identification of useless variables.

3.3.3 PLSR and OLS

Since we benchmark the PLSR outcomes with that of ordinary least squares (OLS), it is interesting to describe the case where these two methods give identical results. Furthermore, as the OLS method is generally known by marketing researchers and the PLSR method not, this could serve as a reference point in better understanding the outcomes. When the number of PCs equals the number of \mathbf{X} variables, PLSR and OLS give identical results (Martens and Martens, 1985). For illustrative purposes we utilize the description given by Helland to formalize the relationship. Formally, the PLS regression coefficients, based on n PC, is given by (Helland, 1988)

$$\beta_{PLS} = \mathbf{K}_n (\mathbf{K}_n^T \mathbf{X}^T \mathbf{X} \mathbf{K}_n)^{-1} \mathbf{K}_n^T \mathbf{X}^T \mathbf{y} \quad (3.16)$$

where $\mathbf{K}_n = (\mathbf{s}, \mathbf{S}\mathbf{s}, \dots, \mathbf{S}^{k-1}\mathbf{s})$. Moreover, define the Krylov subspace $\mathcal{K}_n(\mathbf{S}, \mathbf{s})$ to be $\mathcal{K}_n(\mathbf{S}, \mathbf{s}) = \text{span } \mathbf{K}_n$. In the case where n equals the number of X-variables, denoted by p ($n = p$), in equation (3.16), β_{PLS} is identical to β_{OLS} . In this case the classical variable selection method, based on significance testing can be utilized for β_{PLS} .

3.4 Model Variables

Details on the measurements used in this model are given in the previous chapter. Here, we very briefly discuss the model variables (see Appendix B).

3.4.1 Independent Variables

Reviewing the strategic marketing literature, chapter two develops a model of market-based capabilities incorporating four dimensions, each having several subdimensions, which results in a total of eight components. In this study, we incorporate

the eight components as dimensions of the market-based capabilities construct and relate them simultaneously to several indicators of firm performance. The rationale behind this modeling strategy is that all these subdimensions are closely related and appear to measure the extent to which an organization is market-oriented.

3.4.2 Dependent Variables

We measure wholesale firm performance on five aspects of efficiency and productivity: sales growth, profit growth, overall profitability, labor productivity and cash flow. These are all measured on a seven-point Likert scale, where 1 = “strongly disagree” and 7 = “strongly agree.” These measures are based on those of Lusch and Brown (1996).

3.5 Findings

In this section, we outline the outcomes generated by multivariate partial least squares regression (PLS2). As in the previous chapter, we have 137 datapoints. To derive the outcomes, the data are analyzed in the *UnscramblerTM*, version 9.1. We note that the approximately normally distributed (independent) variables and our sample size form a strength in this study. Naik and Tsai (2000, p. 770) demonstrate that if the independent variables are multivariate normally distributed and the sample size is large, then the relative sizes of the regression coefficients are correctly estimated by PLSR; this is even in the case of a non-linear and unknown link function. To investigate the strength of our proposed method we also estimate the same relationships using standard OLS regression.

Before presenting the regression outcomes, a brief look at the correlation matrix (see Table 3.1) suggests that most variables are significantly correlated. The correlation among the independent variables is moderate, whereas the correlation among the dependent variables is high. Also, the correlation between the independent and dependent variables is low to moderate.

3.5.1 PLS2

PLS2 regression is run with the eight market-based capabilities components as **X**-matrix and the five firm performance indicators as the **Y**-matrix. This analysis is run with full cross-validation and variable selection by jack-knifing. To investigate and detect the optimal number of PCs, we analyze the Root Mean Square Error of Prediction (RMSEP) statistic. The optimal model complexity is indicated when the RMSEP value reaches its minimum. This measure represents the average difference between predicted (\hat{y}) and measured response values (y), and may be expressed as

$$\mathbf{RMSEP} = \sqrt{\frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.17)$$

| | SD | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 |
|-------------|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| CUSTDC (X1) | 1.02 | - | | | | | | | | | | | | |
| COMDC (X2) | 1.24 | .43 | - | | | | | | | | | | | |
| CLC (X3) | .82 | .40 | .57 | - | | | | | | | | | | |
| SLC (X4) | 1.03 | .40 | .42 | .42 | - | | | | | | | | | |
| LOGC (X5) | .79 | .34 | .17 | .28 | .34 | - | | | | | | | | |
| ITC (X6) | 1.27 | .17 | .35 | .22 | .27 | .21 | - | | | | | | | |
| HRC (X7) | .87 | .22 | .35 | .41 | .40 | .22 | .20 | - | | | | | | |
| PC (X8) | .70 | .39 | .27 | .44 | .25 | .39 | .16 | .36 | - | | | | | |
| SG (X9) | 1.25 | .23 | .18 | .19 | .12 | .13 | .18 | .28 | .32 | - | | | | |
| PG (X10) | 1.29 | .15 | .12 | .16 | .18 | .13 | .15 | .34 | .20 | .73 | - | | | |
| OP (X11) | 1.26 | .17 | .13 | .16 | .20 | .15 | .23 | .26 | .21 | .64 | .86 | - | | |
| LP (X12) | 1.11 | .12 | .21 | .26 | .21 | .15 | .23 | .40 | .34 | .64 | .60 | .61 | - | |
| CF (X13) | 1.24 | .16 | .18 | .22 | .27 | .25 | .26 | .32 | .28 | .50 | .68 | .73 | .59 | - |

note: SG is sales growth, PG is profit growth, OP is overall profitability, LP is labor productivity, CF is cash flow, CUSTDC is customer-driven, COMDC is competitor-driven, CLC is customer-linking, SLC is supplier-linking, ITC is information technology, LOGC is logistics, HRC is human-related and PC is people capabilities.

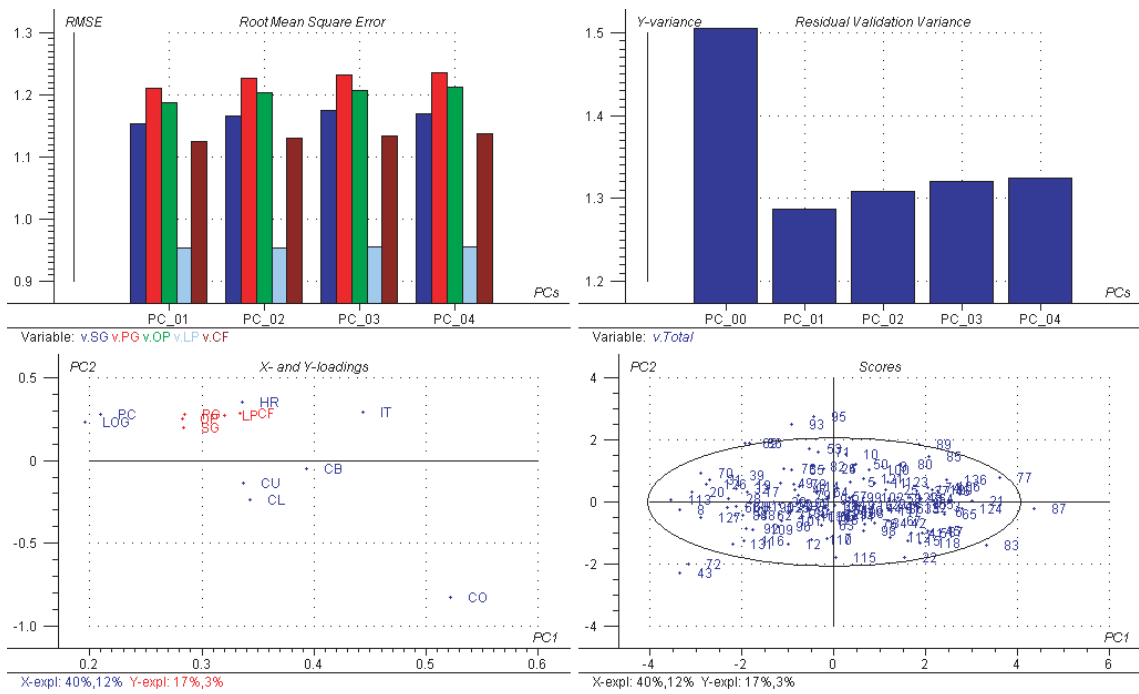
Table 3.1: Descriptive Statistics and Correlations

Before discussing the proposed relationships in detail, we first present some aggregate PLS output, which is shown in figure 3.1. To detect the optimal number of principal components (PCs), we utilize RMSEP. The outcomes are displayed in the upper-left plot of figure 3.1. This plot suggests one latent variable to be the optimal model rank for interpretation for all the independent variables. The plot ‘Residual Validation Variance’ in this figure suggests, in the aggregate, one PC to be the correct complexity of the model; note that PC_00 is the average point in the data set and has to be higher than the different models (PC_01 - PC_11). Looking at the X- and Y-loadings plot, it shows that one PC explains 40% of the variance in \mathbf{X} . Furthermore, this single PC explains 17% of the variation in \mathbf{Y} . In short, the RMSEP plot indicates that, in all cases, the best PLS model requires one PC. 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 3.1 is based on the 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 assume that they may not have an effect on the obtained results.³

Market-Based Capabilities and Sales Growth

The regression outcomes describing the relationship between market-based capabilities and sales growth are outlined in the upper left plot of figure 3.2. The error bars in this plot 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). As can be seen from this plot, the regression outcomes show little uncertainty limits. Furthermore, they do not cross the zero line, indicating a significant effect of all variables on the dependent variable. Hence, all market-based capabilities components positively predict sales growth. In summary, customer-driven ($\beta = .09$),

³As in the previous chapter, we estimated an interaction effects model. The results indicate that none of the combinations (of several components of market-based capabilities) have a strong effect on the financial performance of the firm.



note: SG is sales growth, PG is profit growth, OP is overall profitability, LP is labor productivity, CF is cash flow, CU is customer-driven, CO is competitor-driven, CL is customer-linking, CB is supplier-linking, IT is information technology, LOG is logistics, HR is human-resource and PC is people capabilities.

Figure 3.1: General PLS2 outcomes

competitor-driven ($\beta = .10$), customer-linking ($\beta = .08$), supplier-linking ($\beta = .10$), information-technology ($\beta = .14$), logistics ($\beta = .06$), human-related ($\beta = .12$) and people capabilities ($\beta = .09$) have significant positive effects on sales growth.

Market-Based Capabilities and Profit Growth

The outcomes of the market-based capabilities-profit growth link are shown in the upper right part of figure 3.2. As can be seen from this plot, the regression outcomes suggesting the causal relationship between market-based capabilities and profit growth indicate that all relationships are positive. Furthermore, the error bars do not contain the value zero, indicating significance. Summarizing the plot, customer-driven ($\beta = .09$), competitor-driven ($\beta = .10$), customer-linking ($\beta = .08$), supplier-linking ($\beta = .10$), information-technology ($\beta = .14$), logistics ($\beta = .06$), human-related ($\beta = .12$) and people capabilities ($\beta = .09$) positively predict profit growth.

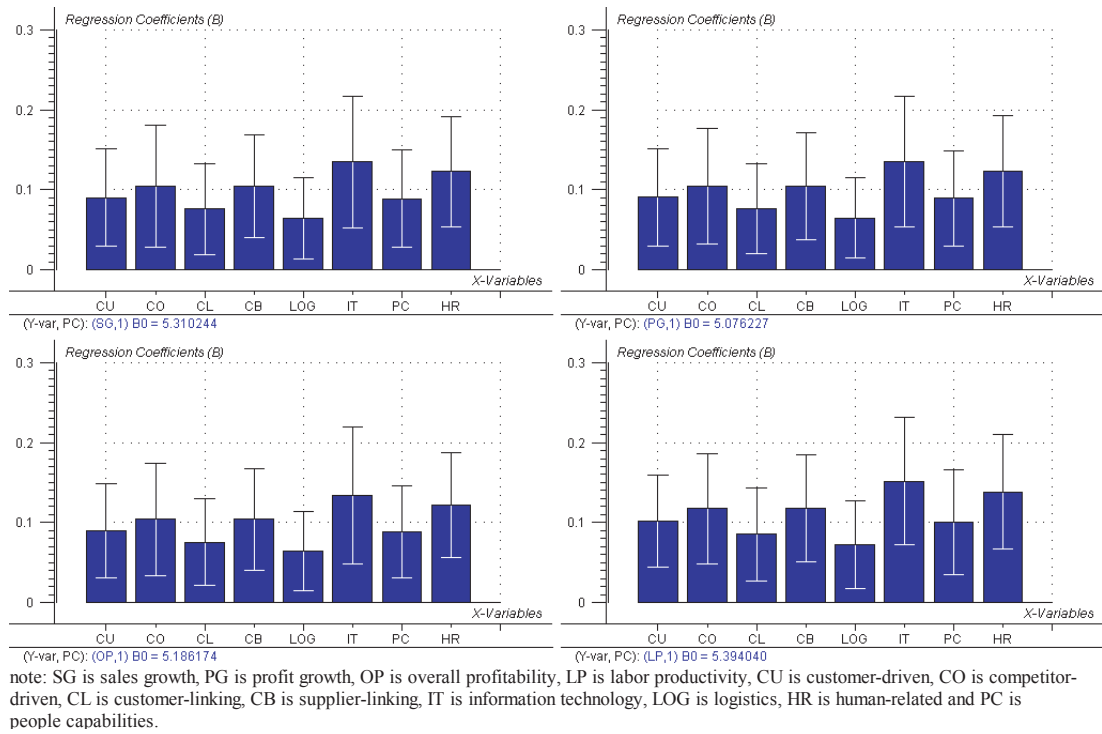


Figure 3.2: PLS regression coefficients: the effect of market-based capabilities on sales growth, profit growth, overall profitability and labor productivity

Market-Based Capabilities and Overall Profitability

The lower-left part of figure 3.2 shows the regression outcomes of the market-based capabilities-overall profitability relationship. All coefficients have their jackknife distributions above zero thus considered statistically significant. Overall profitability is predicted by customer-driven ($\beta = .09$), competitor-driven ($\beta = .10$), customer-linking ($\beta = .08$), supplier-linking ($\beta = .10$), information-technology ($\beta = .13$), logistics ($\beta = .06$), human-related ($\beta = .12$) and people capabilities ($\beta = .09$).

Market-Based Capabilities and Labor Productivity

The regression outcomes with the estimated reliability describing the relationship between market-based capabilities and labor productivity are displayed in the lower right plot of figure 3.2. Summarizing the regression coefficients of this one factor PLSR model, customer-driven ($\beta = .10$), competitor-driven ($\beta = .12$), customer-linking ($\beta = .09$), supplier-linking ($\beta = .12$), information-technology ($\beta = .15$), logistics ($\beta = .07$), human-related ($\beta = .14$) and people capabilities ($\beta = .10$) are significantly related to labor productivity.

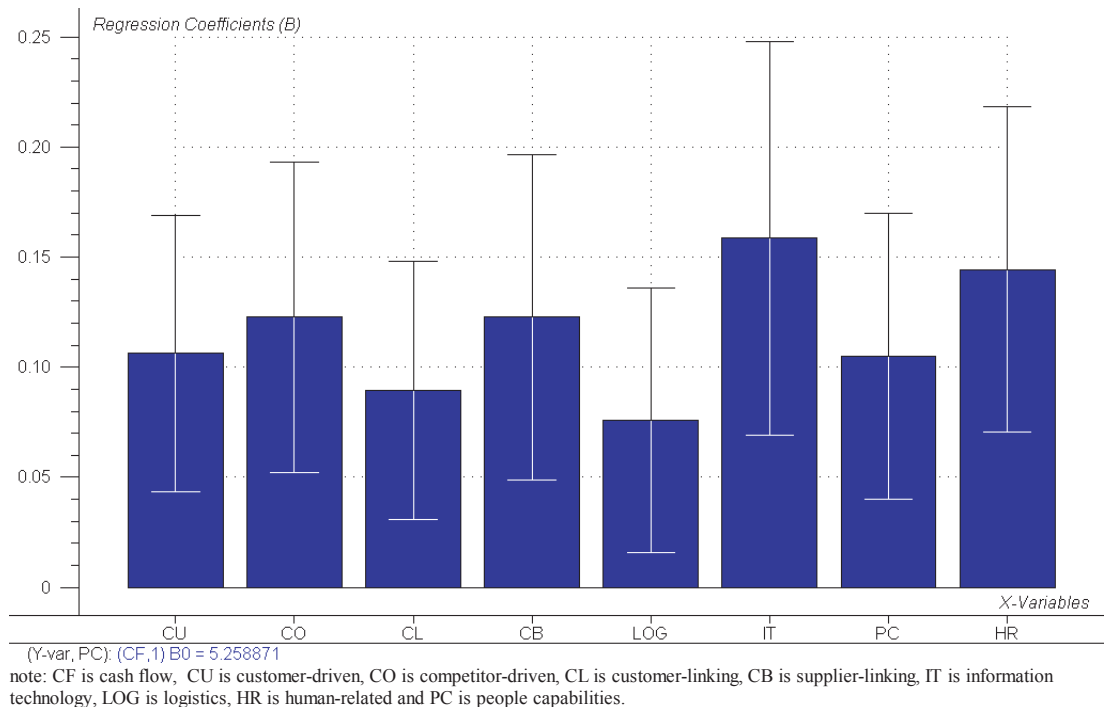


Figure 3.3: PLS regression coefficients: market-based capabilities-cash flow link

Market-Based Capabilities and Cash Flow

Figure 3.3 summarizes the estimated relationship between the market-based capabilities and cash flow. All coefficients have their jack-knife distributions above zero thus considered statistically significant. Furthermore, this plot reveals positive relationships. In summary, cash flow is predicted by customer-driven ($\beta = .11$), competitor-driven ($\beta = .12$), customer-linking ($\beta = .09$), supplier-linking ($\beta = .12$), information-technology ($\beta = .16$), logistics ($\beta = .08$), human-related ($\beta = .14$) and people capabilities ($\beta = .11$).

3.5.2 Ordinary Least Squares Regression

To further demonstrate the strength of PLSR in our case, we estimate an ordinary least squares regression (OLSR) model. Since some components of market-based capabilities are highly correlated, we anticipate poor performance for OLSR. The results of these analyses are shown in table 3.2. In general, the outcomes of this method are not satisfactory. Although all market-based capabilities dimensions are moderately correlated with the five indicators of firm performance, we could only detect a few significant regression coefficients. Furthermore, this method reveals some negative regression coefficients, while these variables are positive correlated with the corresponding dependent variable.

Since our findings indicate a one factor model as the optimal model complexity, we estimate for each dependent variable a model incorporating one independent

| | Dependent Variable | | | | |
|-------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | SG | PG | OP | LP | CF |
| | Coefficient (s.e.) | Coefficient (s.e.) | Coefficient (s.e.) | Coefficient (s.e.) | Coefficient (s.e.) |
| Independent Variables | | | | | |
| Intercept | 5.36** | 5.30** | 5.42** | 5.51** | 5.55** |
| Customer-Driven Capabilities | .08 | .09 | .06 | -.10 | -.17 |
| Competitor-Driven Capabilities | .10 | -.06 | .08 | -.17 | -.09 |
| Customer-Linking Capabilities | .39 | .04 | -.34 | .35 | -.04 |
| Supplier-Linking Capabilities | -.25 | -.15 | .09 | .06 | .25 |
| Logistics Capabilities | -.45 | -.38 | -.39 | -.56* | -.42 |
| Information Technology Capabilities | .20 | .19 | .17 | .22 | .16 |
| Human-Related Capabilities | .23 | .22 | .46 | .43 | .68 |
| People Capabilities | .50 | .65* | .35 | .46* | .07 |
| R ² | .30 | .23 | .26 | .46 | .24 |

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

^a unstandardized regression coefficient.

^b s.e. refers to standard error.

Table 3.2: OLSR outcomes

variable, a composite variable called market-based capabilities; hence, dependent variable = $f(\text{Market-Based Capabilities})$. The results confirm our PLSR findings. Market-based capabilities have a positive significant influence on sales growth ($\beta = .62$, $p \leq .00$ and $R^2 = .10$), profit growth ($\beta = .58$, $p \leq .00$ and $R^2 = .08$), overall profitability ($\beta = .60$, $p \leq .00$ and $R^2 = .09$), labor productivity ($\beta = .66$, $p \leq .00$ and $R^2 = .13$) and cash flow ($\beta = .75$, $p \leq .00$ and $R^2 = .14$).

3.6 Discussion

The outcomes of this study provide support for the configurational-based view, which seeks to integrate the two dominant views in strategic marketing: the market-based view (MBV) and the resource-based view (RBV). The configurational-based view considers both the firm's heterogeneous bundles of resources (RBV) and the issue of heterogeneous demand (MBV), and is therefore more realistic. Utilizing a configurational-based perspective, the previous chapter develops a model of market-based capabilities. Our analysis provides additional support for this model and framework. In all cases, we find one PC indicating that the eight market-based capabilities are part of one underlying dimension. These findings also support Day's (1994) thesis that both marketing or outside-in capabilities and operations or inside-out capabilities are crucial for the development of market-based competition. Integrating both the inside-out and outside-in views is also recently considered to be a potentially fruitful avenue for research (Ho and Tang, 2004; Vargo and Lusch, 2004). Following a configurational-based perspective has two major implications for the field. First, marketing and (operations) management scientists have to cooperate to develop more realistic, and possibly more complex, models. Since the two

streams seem to emphasize different problems, this will be a challenge. Furthermore, analyzing frameworks that enables competing marketing and management strategy options to be traded off on the basis of financial and nonfinancial indicators is rather complex. Also, obtaining the model input may become a very challenging task.

The results described in the previous section highlight some of the unique insights that emerge from this way of modeling (using soft methods). Although our analysis is rather explorative in nature, it demonstrates that marketing-based capabilities (customer-driven, competitor-driven, supplier-driven, technology-monitoring, customer-linking and supplier-linking capabilities) indeed positively predict business performance. These results confirm previous research (Narver and Slater, 1990; Kalwani and Narayandas, 1995). However, these findings are not in line with some previous results (Christensen and Bower, 1996; Voss and Voss, 2000) that indicate that customer-driven capabilities are not related to business performance. Our study indicates that other market-driven and market-based capabilities are indeed more evident to business performance than customer orientation. This suggests that although customer-driven capabilities lead to positive performance outcomes, other market-based capabilities have a stronger effect.

Comparing the outcomes in this chapter with that of chapter 2 we see that in both studies human-related capabilities show the highest correlation with various indicators of business performance. A differentiating factor of this study is that it provides more detailed outcomes. For example, our analysis suggests that although human-related capabilities are strongly related to business performance, information technology capabilities have the greatest impact.

We have presented an algorithm/method to conduct operational level modeling, multivariate partial least squares regression. This method provides the marketing manager with a tool to develop models that appropriately reflect the given data and theory. An advantage of our analytical method is the ability to relate a high number of (collinear, noisy and possibly even incomplete) independent variables with a (high) number of (collinear and noisy) dependent variables. This may open the door for (marketing) researchers seeking to relate a large number of (highly) related business processes, competencies, capabilities or resources to some outcome performance. For example, in Srivastava et al.'s (1999) framework, marketing processes are considered to be essential in delivering superior market performance. However, marketing processes are many and highly interrelated and standard methods, based on ordinary least squares, are not sufficient in this case.

Another advantage of PLSR is the number of distracted components and the obtained simplicity of the (optimal) model. This method can fit the data at hand with fewer components than PCR (Frank and Friedman, 1993) resulting in more parsimonious models. This is also found in this study. The PLSR analysis confirms the proposition that the market-based capabilities construct is measured by one underlying latent factor. The arguments for the relatively better fit of PLSR (above PCR) is provided by Frank and Friedman (1993). Another advantage of PLSR is its simplicity. The basic idea behind this method is simple to understand and very appealing, especially for practitioners.

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, Martens and Martens (2000) conclude with a cautious remark: “since the perturbations are expected to be primarily of nonrandom character, such statistical summaries were considered to be of limited value, and fully misleading if presumed to yield probabilistic “95% confidence regions.”” However, PLSR is generally used when many independent variables and high (multi)collinearity among these variables exist. In this case, as argued by Höskuldsson (2003), the traditional approach to selecting variables, based on significance testing, has some basic defects (this is also shown in this study). Therefore, although future research deriving confidence intervals for the PLSR parameters is needed, the pragmatic method, based on jack-knifing, proposed by Martens and Martens (2000) and used in this study, seems to be a strong alternative variable selection method.

Further research is needed relating the market-based capabilities model to other plausible outcomes, such as service quality and customer satisfaction. For example, Quinn, Doorley and Paquette (1990) suggest that “a maintainable advantage usually derives from outstanding human skills, logistics capabilities, knowledge bases, or other service strengths that competitors cannot reproduce and that lead to greater demonstrable value for the customer” (p. 60). Srivastava et al. (2001, p. 796) call for future research by stating that “both the RBV and marketing researchers must commit to carefully and systematically identifying and documenting how particular market-based assets and capabilities contribute to generating and sustaining specific forms of customer value.”

3.7 Conclusions

As this study indicates, ordinary least squares regression methods, based on ordinary least squares, do not give the management a strong method to derive (operational) improvements, since the relevant capabilities in a business, such as marketing, supply chain activities and information technology, are frequently highly interconnected, or even depend on each other. However, as demonstrated by this study, PLSR provides management with a strong and simple tool to detect the degree to which different, highly correlated variables have an effect on several operational indicators of firm performance. Although our analytical method seems to perform well in this case, future research is needed to further determine whether this method is also valuable in other cases.