THE IMPACT OF ACCOUNTING-BASED INFORMATION ON THE FINANCIAL BETA: CASE FOR CEMENT INDUSTRY IN TURKEY

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In financial theory, the cost of equity is defined as a return that stockholders require for a company. It has a vital importance for corporations in evaluation of investment opportunities. There are several methods to calculate the cost of equity including Capital Asset Pricing Model (CAPM). The CAPM is a commonly used method but it has a major restriction. It can be used only for publicly traded corporations not for non-public corporations because it requires stock return data to estimate Financial Beta. When the stock price is not available for a firm, finance literature suggests that Accounting Beta can be used as a proxy of financial beta to estimate the cost of equity. Most of researchers have aimed to find a relationship between financial beta and accounting variables. However, they used correlation or regression based approaches.

The purpose of this study is to evaluate the impact of accounting-based information on the financial Beta through a non-linear approach, namely Support Vector Machines (SVM). Most of the studies in finance literature focus on the linear relationship between Betas and accounting variables and the results reveal that the explanatory powers of linear models are limited. To avoid this problem, this study applies SVM as an alternative method to analyze the size of impact of accounting variables on the financial Betas rather than estimating a linear model. Based on Statistical Learning Theory and Structural Risk Minimization Principle, the SVM algorithms are able to solve regression problems without getting stuck in local minima. They achieve the global solution by transforming the regression problem into a quadratic programming (QP) problem and then solving it by any QP solver. Recently, SVM-based algorithms have been developed very rapidly and have been applied to many areas. Finding global solution and having higher generalization potential constitute the major advantages of the SVM algorithms over other regression techniques.

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In this study, the accounting information is represented by current ratio, quick ratio, net profit margin, assent turnover, return on assets, return on equity, financial leverage and logarithmic total assets over 2005-2014 period. In addition to that, financial betas of cement firms traded in Borsa Istanbul (BIST) are calculated for each year. The result of the study illustrates that financial leverage, the size and asset turnover have the highest impact on financial beta, respectively.

Keywords: Accountinf Beta, Financial Beta, CAPM, Support Vector Machine

Introduction

In financial theory, the cost of equity is defined as a return that stockholders require for a company. It has a vital importance for corporations in evaluation of investment opportunities. There are several methods to calculate the cost of equity including Capital Asset Pricing Model (CAPM). The CAPM is a commonly used method but it has a major restriction. It can be used only for publicly traded corporations not for non-public corporations because it requires stock return data to estimate Financial Beta. When the stock price is not available for a firm, finance literature suggests that Accounting Beta can be used as a proxy of financial beta to estimate the cost of equity. Most of researchers have aimed to find a relationship between financial beta and accounting variables. However, they used correlation or regression based approaches.

In empirical sense, Beaver et al. (1970) analyzed relationship between beta and accounting variables. The empirical results of the study shows that there is a statistically significant relationship with beta and accounting variables. On the other hand, Gonedes (1973, 1975) found contradictory results. Blume (1971), Bogue (1973) indicate that the explanatory power of accounting-based models is not statistically significant.

This study applies Support Vector Machines (SVM) as an alternative method to analyze the size of impact of accounting variables on the financial betas rather than estimating a linear model. Most of the studies in finance literature focus on the linear relationship between Betas and accounting variables and the results reveal that the explanatory powers of linear models are limited.

In this study, the accounting information is represented by current ratio, quick ratio, net profit margin, assent turnover, return on assets, return on equity, financial leverage and logarithmic total assets over 2005-2014 period. In addition to that, financial betas of cement firms traded in Borsa Istanbul (BIST) are calculated for each year. The result of the study illustrates that financial leverage, the size and asset turnover have the highest impact on financial beta, respectively.

Methodology

Support Vector Machine (SVM) regression models have been employed for modeling nonlinear dynamics for various purposes successfully due to their peculiar properties namely high generalization capability and the assurance of global minimum (Vapnik, 1995; 1998a; 1998b; Smola, and B. Schölkopf, 1998). Based on the Statistical Learning theory and the Structural Risk Minimization principle, SVM approaches solve any regression problems by transforming the regression problem into a quadratic programming (QP) problem. Recently, SVM-based algorithms have been developed very rapidly and have been applied to many areas (Cristianini, and Taylor, 2000; Schölkopf, et al., 1999; Colin and

Yiming, 2011). In this subsection, the support vector machines (SVM) regression algorithm, used in this study, is described briefly. Given a set of N training points as $\mathfrak{D} = \{\mathbf{t}_i, y_i\}_{i=1}^{N}$, where $\mathbf{t}_i \in \mathbb{R}^R$ and $y_i \in \mathbb{R}$, the problem is to obtain a regression model that captures the relationship between the input and output data points as accurate as possible. For this purpose, we have employed the so-called ε-SVR algorithm that treats the regression problem as as optimization problem and tries to find an appropriate SVM model. The primal form of a SVM regression model is given by (1), which is a linear model in an higher dimensional feature space $\boldsymbol{F}$:

$$\hat{y}(\mathbf{x}_i) = \langle \mathbf{w}, \mathbf{\Phi}(\mathbf{x}_i) \rangle + b \tag{1}$$

where $\mathbf{w}$ is a vector in the feature space $\boldsymbol{F}$, $\mathbf{\Phi}(.)$is a mapping from the input space to the feature space, b is the bias term and $\langle , \rangle$ is the inner product operation in the feature space. Instead of the primal form of the SVM regression model, its dual form as given below is utilized:

$$\hat{y}(\mathbf{x}_i) = \sum_{j=1}^{N} \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) + b, \tag{2}$$

where α_j's are the coefficients of each training data point and $K(\mathbf{x}_i, \mathbf{x}_j)$ is a kernel function that handles the inner product operation in the feature space, i.e. $K(\mathbf{x}_i, \mathbf{x}_j) = \langle \mathbf{\Phi}(\mathbf{x}_i), \mathbf{\Phi}(\mathbf{x}_j) \rangle$. Hence the explicit form of $\mathbf{\Phi}(.)$ is not needed. In this study, we have used the Gaussian kernel function given by,

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}}, \tag{3}$$

where $\|.\|$ is the Euclidean norm and σ is the width parameter. In the dual SVM model, a training point $\mathbf{x}_j$ corresponding to a non-zero α_j value is referred to as the *support vector*. Turning back to the regression problem, the standard ε-SVR algorithm employs the Vapnik's ε -insensitive loss function,

$$L(\varepsilon, y, \hat{y}) = \begin{cases} 0 & y - \hat{y} \leq \varepsilon \\ y - \hat{y} & y - \hat{y} > \varepsilon \end{cases} \tag{4}$$

and formulates the regression problem in primal space as follows:

$$\min_{\mathbf{w}, b, \boldsymbol{\xi}, \boldsymbol{\xi}^*} \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^{N} (\xi_i + \xi_i^*) \tag{5}$$

subject to the constraints,

$$\begin{array}{ll} y_i - \mathbf{w}^T \mathbf{\Phi}(\mathbf{t}_i) - b \leq \varepsilon + \xi_i, & i = 1, \ldots, N \\ \mathbf{w}^T \mathbf{\Phi}(\mathbf{t}_i) + b - y_i \leq \varepsilon + \xi_i^*, & i = 1, \ldots, N \\ \xi_i, \xi_i^* \geq 0 & i = 1, \ldots, N \end{array} \tag{6}$$

where ξ_i's and ξ_i^*'s are slack variables, ε is the upper value of the error tolerance for the output and C is a regularization parameter that provides a compromise between the model complexity and the degree of tolerance to the errors larger than ε. The dual form of the optimization problem becomes a quadratic programming (QP) problem as:

$$\min_{\boldsymbol{\beta},\boldsymbol{\beta}^*} \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\beta_i-\beta_i^*)(\beta_j-\beta_j^*)\boldsymbol{\Phi}^T(\mathbf{t}_i)\boldsymbol{\Phi}(\mathbf{t}_j)+\varepsilon\sum_{i=1}^{N}(\beta_i+\beta_i^*)-\sum_{i=1}^{N}y_i(\beta_i-\beta_i^*) \tag{7}$$

subject to the constraints,

$$\sum_{i=1}^{N}(\beta_i^*-\beta_i)=0 \text{ and } 0\le\beta_i,\beta_i^*\le C, \qquad i=1,\dots,N. \tag{8}$$

Solution of the QP problem gives the optimum values of β_i's and β_i^*'s. Moreover, b in the dual model is determined in amanner such that the condition $y_i-\hat{y}(\mathbf{x}_i)=\varepsilon$ is satisfied for each support vector $\mathbf{x}_i$ for which the condition $0\le\beta_i,\beta_i^*\le C$ is hold. Definition of α_j as $\alpha_j=\beta_j-\beta_j^*$, for $j=1,\dots,N$ leads to the dual SVM model as given by (10). Furthermore, if the support vectors are considered only, then the model becomes,

$$\hat{y}(\mathbf{x}_i)=\sum_{j=1}^{\#SV}\alpha_j K(\mathbf{x}_i,\mathbf{x}_j)+b \tag{9}$$

where #SV stands for the number of support vectors in the model [4-6]. The SVM model (18) is sparse in the sense that the whole training data are represented by only support vectors. The parameters of the SVM model are the error tolerance ε at the output, the regularization parameter C and the width parameter σ. The major advantage of the ε-SVR algorithm is that it allows for determining the maximum total training error beforehand by choosing a proper ε value.

Findings

Table 1. The Size of Impact of Accounting Variables on Financial Beta - Support Vector Machines Simulations

Simulations	Asset Turnover	Current Ratio	Quick Ratio	Net Profit Margin	Log(Asset)	Financial Leverage	ROA	ROE
Result - 1	16.40%	6.00%	8.10%	3.60%	26.60%	30.10%	5.30%	3.90%
Result - 2	17.00%	6.50%	8.50%	4.90%	17.10%	41.50%	2.60%	1.90%
Result - 3	17.90%	6.50%	8.90%	3.60%	27.40%	26.20%	5.50%	3.90%
Result - 4	21.50%	7.10%	8.90%	3.10%	28.60%	23.00%	4.70%	3.10%
Result - 5	20.00%	6.90%	9.10%	3.30%	28.00%	24.10%	5.10%	3.50%
Result - 6	17.90%	6.50%	8.90%	3.60%	27.40%	26.20%	5.50%	3.90%
Result - 7	16.00%	5.80%	7.70%	3.50%	26.10%	32.20%	5.00%	3.80%
Result - 8	15.10%	5.90%	6.70%	2.50%	20.20%	44.10%	3.30%	2.20%
Result - 9	20.10%	8.50%	5.30%	0.00%	22.50%	40.20%	0.70%	2.60%
Result - 10	15.50%	5.80%	6.50%	2.60%	22.20%	41.20%	3.60%	2.60%
Result - 11	20.60%	7.00%	9.00%	3.20%	28.20%	23.70%	5.00%	3.30%
Result - 12	22.70%	7.50%	7.70%	2.90%	20.80%	32.40%	4.40%	1.70%
Result - 13	17.40%	6.40%	8.70%	3.60%	27.20%	27.20%	5.50%	4.00%
Result - 14	20.30%	7.70%	5.50%	0.30%	24.80%	36.80%	3.10%	1.60%
Result - 15	14.70%	6.00%	7.50%	3.20%	16.50%	47.10%	3.00%	1.90%
Result - 16	15.40%	5.80%	6.50%	2.50%	22.00%	41.70%	3.50%	2.60%
Result - 17	16.30%	5.90%	8.00%	3.60%	26.50%	30.60%	5.20%	3.90%
Result - 18	15.30%	5.90%	6.60%	2.50%	21.10%	42.90%	3.40%	2.40%
Result - 19	15.50%	5.60%	6.60%	3.00%	23.90%	38.20%	4.10%	3.10%
Result - 20	19.10%	6.80%	9.10%	3.50%	27.70%	24.80%	5.30%	3.70%
Averages	17.74%	6.51%	7.69%	2.95%	24.24%	33.71%	4.19%	2.98%
Max	22.70%	8.50%	9.10%	4.90%	28.60%	47.10%	5.50%	4.00%
Min	14.70%	5.60%	5.30%	0.00%	16.50%	23.00%	0.70%	1.60%

Table 1 illustrates that financial leverage, the size and asset turnover have the highest impact on financial beta, respectively. On the average the size impact of financial laverage is is 33.71%, the size (Log(Asset)) is 24.24% and asset turnover is 17.74%. Almost 80% of financial beta is influenced by these three accounting information groups for cement firms traded in Borsa Istanbul.

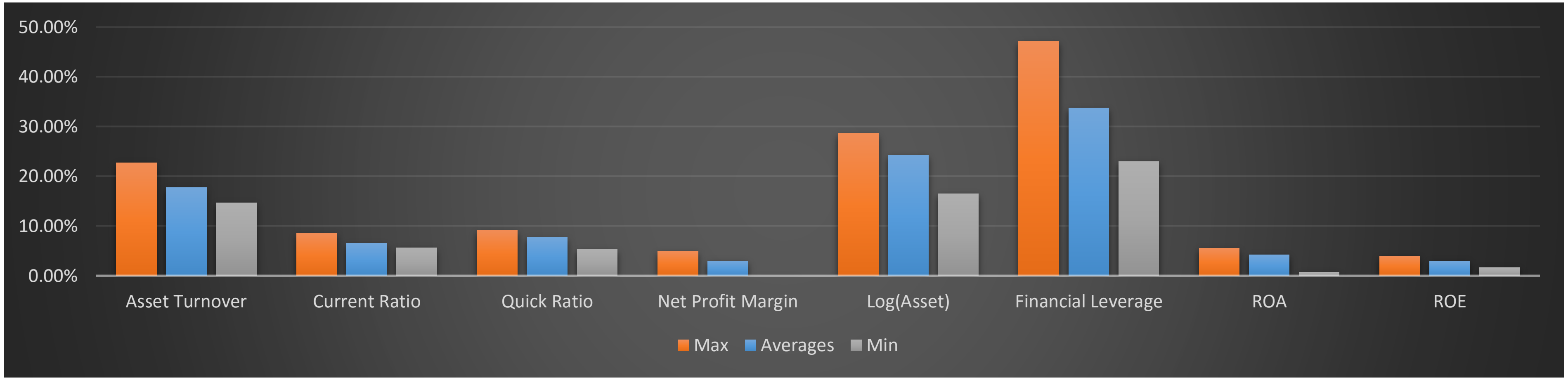

Figure 1. Maximum, Minimum and Averages of Support Vector Machines Simulations

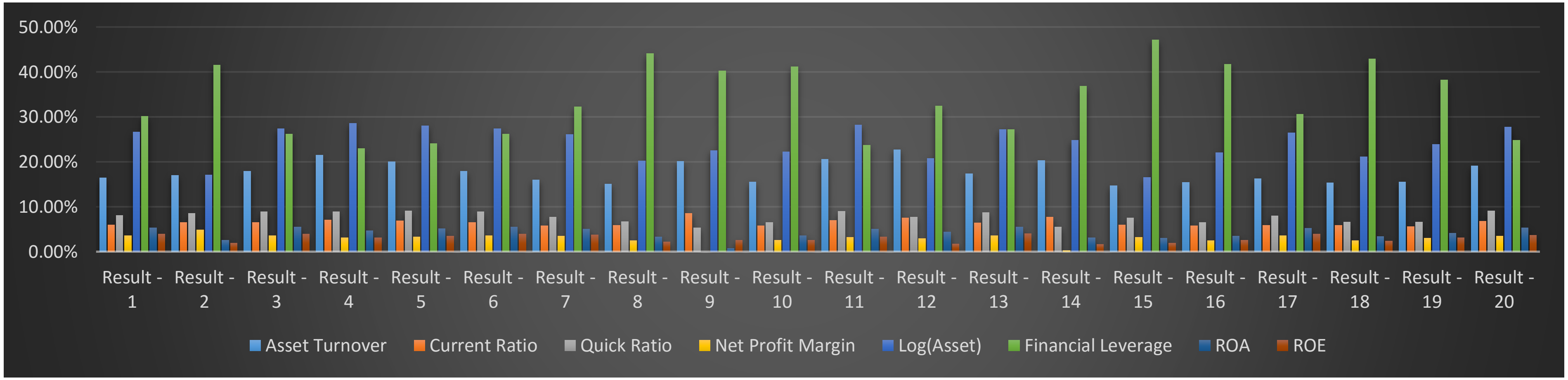

Figure 1. Support Vector Machines Simulations Results for Each Accounting Variable

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