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Financial Ratios as Predictors of Firms' Industry Branch

Exploring the Impact of Governmental Incentives on Regional Growth

Framework for an Effective Decision Support System. Part I

Nya Finansiella Instrument och Deras Användning i Företagens Kapitalförvaltning

Onko laskentatoimi (kirjanpito) vain rahaprosessin kuvausta?

Julkisen liikelaitoksen liiketaloudellinen ja yhteiskunnallinen päämäärä. Esimerkkinä Suomen Valtionrautatiet

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Financial Ratios as Predictors of Firms’ Industry Branch*

1. INTRODUCTION

1.1 Problem Statement

Financial ratios are commonly used for intra-industry comparisons. In financial statement analysis a firm’s performance and financial status are frequently evaluated in relation to other firms in the same branch of industry, or in relation to industry averages.¹ This common practice obviously has economic repercussions. Empirical evidence by Lev (1969) and Frecka & Lee (1983)² indicates that firms tend to adopt policies which direct their financial ratios towards industry means. This behavior would increase the efficiency of an economy only if the industry averages were optimal as targets, which hardly is guaranteed.

Salmi & Dahlstedt & Luoma & Laakkonen (1986) (SDLL (1986) from here on) showed that intra-industry comparisons of firms is ill-advised for several of the industries. This results from the finding that many industry branches are not homogenous in terms of financial ratios. The finding was based on five financial ratios from a sample of forty-two publicly traded Finnish industrial firms covering the period from 1974 to 1984.

* Kiitämme Paulon Säätiötä saamastamme tuesta.

¹ Besides comparing a firm’s financial ratios to corresponding industry averages it is quite common to evaluate a ratio relative to the distribution of the ratio within the industry. The underlying idea in this practice is trying to assess whether a (negative or positive) deviation from the industry mean is significant or not. This has given rise to numerous papers on the distributional properties of accounting ratios. See e.g. Deakin (1976), Bougen & Drury (1980), Lee (1985), Buijink & Jegers (1986). Also see Barnes (1982), Horrigan (1983), and Barnes (1983).

² Also see Brown & Ball (1967), and Foster (1986) for discussion on industry and economy components of financial ratios.
The weakness of the congruence between industry classification and firm characteristics raises two objectives for our study. First, we question the validity of official industry classifications. Second, the risk of making biased financial performance evaluations is at issue. The basic problem of the current paper is whether or not the central financial ratios have levels which are characteristic of different industry branches. This problem can be restated as whether it is possible to predict a firm’s industry branch from its central financial ratios. If predicting industry branch on the basis of a firm’s financial ratios is possible, the next question is whether any single financial ratio predicts (explains) industry branches to a significant degree.

From SDL (1986) it is to be expected that the ability of financial ratios to predict industry branches will in most cases be weak, with some exceptions.

1.2 Approach

Basically, the problem concerns the relationship between the dependent variable (industry branch) and the explanatory variables (financial ratios). There are several potential approaches for studying such relationships. One possibility would be to analyze the correlations between the dependent and explanatory variables using dummy-variable techniques. The second potential approach would be to regress the financial ratios to the industry branch. In these approaches, however, the categorical nature of the dependent variable becomes problematic. Industry branch is not even an ordered set as are failure/ non-failure in bankruptcy research or bond-ratings in bond-rating studies.\(^3\)

The third potential approach is discriminant analysis. Because of the nature of the dependent variable this method is preferable. Compared to the correlation and regression approaches using discriminant analysis means foregoing the standard statistical measures for evaluating the significance of the relationship.\(^4\) This choice will thus mean that we have to develop a procedure for evaluating the degree of discrimination. We are searching for a minimum set of financial ratios (predictors) which provide a better discrimination of industry branches than a random choice.

Our problem is multi-dimensional, because the explanatory variables involve three dimensions. These dimensions are the financial ratios, the firms, and the years. Usually, such dimensionality is reduced (e.g. in studies on factoring financial ratios) by resigning to cross-sections or averaging. In order to avoid the en-

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\(^3\) See Foster (1986), Ch. 14 and 15, and Watts & Zimmerman (1986), Ch. 5 for further references.

\(^4\) The implications of this fact are not always fully appreciated when using discriminant analysis e.g. in bankruptcy prediction.

suing loss of information we do not take this avenue. Instead, we pool the observations over the years and the firms. It must be noted, however, that this procedure leads to biased estimates, if the discrimination is not stable over the years. Therefore, it is necessary to test whether the discrimination is stable (which, indeed, is the case).

For the actual estimation the initial set of financial ratios must be chosen together with the firms and the time span. We use the same data-base as in SDL (1986). Thus the initial set of financial ratios will consist of labor intensiveness, return on assets, leverage, quick asset ratio, and inventory turnover in days. The firms in the sample are the forty-two industrial publicly traded Finnish firms, and the time-span is from 1974 to 1984.

Our selection of the firms admittedly poses a problem. Many of the Finnish publicly traded firms are multi-industry firms. The choice was based upon their importance in the Finnish economy, and the ready availability of the data. The research methodology is not affected by this fact, but it may have bearing on the results.

2. PREDICTION OF INDUSTRY FROM A COMBINATION OF FINANCIAL RATIOS

2.1 Model

As stated in Introduction we are basically interested in the extent to which the central financial ratios have patterns which are characteristic of and distinct between different industries. Logically, if the industries were perfectly distinct in the financial ratios sense, the financial ratios of a single-industry firm would perfectly define its industry branch. Consequently, we will study to ability of financial ratios to predict the industry branch of the firm.

In order to predict the industry branch of a firm from a set of financial ratios we specify the following discriminant analysis model:

(1) \[ \max_h Z = a_h + b_{h,1}X_{i,t,1} + \ldots + b_{h,j}X_{i,t,j} \]


7 Discriminant analysis is a well-known statistical method in business studies. In particular, it has successfully been applied in predicting corporate failure. The single-variable approach of Beaver (1966) and the multivariate model by Altman (1968) are the classics. See Zavgren (1983) for a review of the state of the art. Also see Taffler (1982) for its quality in the statistical aspects, and Eisenbeis (1977) for the pitfalls in applying discriminant analysis. For recent studies on corporate failure see e.g. Peel & Peel & Pope (1986), and Goudie (1987). Also see Rushinek & Rushinek (1987) for assessing the status of a prospective borrower with discriminant analysis.
where

\[ Z = \text{the discriminant Z-score} \]

\[ X_{i,t,j} = \text{the value of financial ratio } j \text{ for firm } i \text{ in year } t \quad (i=1,...,I; \ t=1,...,T; \ j=1,...,J) \]

\[ a_h = \text{the constant for the discriminant function of industry branch } h \quad (h=1,...,H) \]

\[ b_{h,j} = \text{the coefficients of the discriminant function of industry branch } h \]

In model (1) a distinct set of coefficients is estimated for each category (industry branch). In applying the model for prediction an observation is classified into the category yielding the highest Z-score for the observation.\(^8\)

### 2.2 Database

Empirically, there are ten \((H = 10)\) industry branches in our database. In comparison, bankruptcy studies involve a dichotomous ordered dependent variable (failure/nonfailure). Bond-rating studies involve multiple categories (often nine), but these categories are ordered. (From the poor C to the excellent AAA). In the case of industry branches, the dependent variable is truly categorical.

The five \((J = 5)\) financial ratios from SDLL (1986) are used, as introduced in the previous chapter. The forty-two \((I = 42)\) publicly traded industrial Finnish firms and the years from 1974 to 1984 \((T = 11)\) bring about two additional dimensions. Instead of averaging or reverting to cross-sections we pool the observations.\(^9\) Thus any observation of the explanatory variables can be delineated by

\[(2) \quad X: (X_{i,t,1}, X_{i,t,2}, \ldots, X_{i,t,J})\]

\(^8\) Alternatively, the model can be presented as the following classification rule. Assign the observation

\[ X_0: (x_{0,t,1}, \ldots, x_{0,t,J}) \]

to category \(g\) if

\[ U_g X_0 = \max \ U_h X_0 \quad h = 1, \ldots, H \]

where

\[ U_h X_0 = a_h + b_{h,1} x_{0,t,1} + \ldots + b_{h,J} x_{0,t,J} \]

As is well-known in statistics, discriminant analysis is based on the assumptions of normality, and the equality of variances and covariances (and hence the correlations) in the different categories. Furthermore, it is assumed that the costs of misclassifications are equal. The classification rule follows from minimizing the total costs. See Hawkins (1982), pp. 3—7 and Srivastava & Carter (1983), p. 240. An observation is classified into the category which results in the smallest Mahalanobis distance for the observation. Mahalanobis distance also takes into account the correlations between the variables in addition to their variances. The classification rule thus is a minimum distance rule using the generalized distance concept.

\(^9\) By pooling the observations we are able to utilize the maximum amount of information. This fact outweighs the statistical problems involved in pooling. See Richardson & Davidson (1984), and their references for the statistical problems. In particular, the potential autocorrelation within the financial ratios, caused by the pooling, tends to inflate the significance levels of statistical tests.
In the pooled set of the observations index $t$ first runs over the years and $i$ then over the firms. Hence, there are 462 observations in applying model (1).

Appendix A delineates the observations by giving a few statistics as well as the correlations between the financial ratios.

2.3 Results

Denoting $a(h)$ and $b(h,j)$ (where $h=1,\ldots,H$) in model (1) reflects the fact that a separate set of coefficients is estimated for each industry branch.\(^{10}\) In other words ten discriminant functions are estimated, and used for prediction. An observation is classified (discriminated) into the industry branch yielding the highest $Z$-score for the observation.

The estimated discriminant functions for the five-variable model are given in Appendix B. It also includes the results used in discriminating with a single variable at a time, which is taken up in a later chapter.

The discriminant functions were estimated and used to predict the industry branch in the case of each of the 462 observations. The percentages of the correct predictions are given below. The temporal stability of these results was found to be high.\(^{11}\)

<table>
<thead>
<tr>
<th>TOL 31</th>
<th>17/44 = 38.6%</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOL 32</td>
<td>18/55 = 32.7%</td>
</tr>
<tr>
<td>TOL 34</td>
<td>59/132 = 44.7%</td>
</tr>
<tr>
<td>TOL 35</td>
<td>6/22 = 27.3%</td>
</tr>
<tr>
<td>TOL 36</td>
<td>16/22 = 72.7%</td>
</tr>
<tr>
<td>TOL 38</td>
<td>22/77 = 28.6%</td>
</tr>
<tr>
<td>TOL 61</td>
<td>58/66 = 87.9%</td>
</tr>
<tr>
<td>TOL 62</td>
<td>13/22 = 59.1%</td>
</tr>
<tr>
<td>TOL 71</td>
<td>10/11 = 90.9%</td>
</tr>
<tr>
<td>TOL 83</td>
<td>3/11 = 27.3%</td>
</tr>
<tr>
<td>Overall</td>
<td>222/462 = 48.1%</td>
</tr>
</tbody>
</table>

The industry classification used in the above is the Standard Industry Classification. The classification is called the TOL classification in Finland.\(^{12}\) Appendix C gives the key to the TOL codes.

---

\(^{10}\) This procedure gives better prediction than estimating a single set of discriminant coefficients.

\(^{11}\) The stability of the results was tested by dividing the observations into two subsamples made up by the odd and the even years, and estimating the results from these subsamples. No differences were found, and thus the stability of the estimates is established. Furthermore, the outliers occurring in the sample do not affect the results. This was established by comparing the estimates to estimates from a sample with the outliers omitted.

The five financial ratios discriminated the industry branch correctly in 222 cases out of the 462. This means that 48.1 per cent were predicted correctly.

As was to be expected from SDLL (1986) the prediction was significantly better for observations from relatively more homogeneous industry branches. For example, the wholesale trade firms (TOL 61) are classified into the correct industry branch on the basis of the five financial ratios in 87.9 per cent of cases. On the other hand in the case of manufacture of fabricated metal products, machinery and equipment (TOL 38) only 28.6 per cent of the observations are correctly predicted by the relevant discriminant function. This is in keeping with our earlier results in SDLL (1986).\(^\text{13}\) Comparison between TOL 61 firms is clearly better warranted than comparisons between TOL 38 firms, where the danger of misleading intra-industry comparisons is very high. (This reasoning can, naturally, be extended to the other industry branches as well.)

On the basis of the above we put forward that the percentages of the correct predictions serve as a relative index of the safety of intra-industry financial statement analysis comparisons between firms (or comparisons to industry averages). As an example, the estimates of the index where low for TOL 38 and high for TOL 31, while the overall index was 48.1 per cent.

### 3. BENCHMARK FOR EVALUATING THE RESULTS

Intuitively the results seem to indicate that as a combination the (five) financial ratios do indeed have some predictive ability. Two questions remain, however.

First, the strength of the discrimination is at issue. Unfortunately, discriminant analysis does not include such statistics as the coefficient of determination ($R^2$) of regression analysis. Therefore, a benchmark must be developed in order to have some idea of the level of the discrimination. This question is taken up in the current chapter.

Second, intra-industry comparisons in financial statement analysis are (usually) based on one financial ratio at a time, not on combinations of financial ratios. Hence, the question arises whether, and to what extent, the individual financial ratios predict the industry branches. This question is taken up in the next chapter.

Consider the question of the statistical significance of the results. It is obvious that a discriminant function has predictive power if it discriminates better between the different categories (industry branches in our case) than does a random choice. Therefore, we have to establish in how many cases the industry branch would be correct if chosen randomly, and then compare the 222 cases out of 462 to this figure.

\(^\text{13}\) This marked variation of homogeneity of industry branches is in line with the results of Sudarsanam & Taffler (1982, pp. 13 and 18) on U.K. data.
The different industry branches have a different number of firms (and thus a different number of observations) in them. The best comparable random choice should consequently be based on the proportional frequencies for the industry branches. Thus we apply a proportional chance criterion.

Denote

\( M_h = \) the number of observations \( X \) (as defined by (2)) in industry branch \( h \)

\( H = \) the number of industry branches

\( K = \) the total number of observations (i.e. \( I \times T \))

\( C = \) the total number of correctly classified observations applying the proportional chance criterion

Starting from the relative frequencies of the observations in an industry branch the following reasoning can be applied to give the expected number of observations correctly classified by a stratified random choice.

The relative frequencies of observations in the industry branches are respectively

\[ (3) \quad \frac{M_1}{K}, \frac{M_2}{K}, \ldots, \frac{M_H}{K} \]

If each of the observations is classified into the industry branches randomly in proportion to the relative frequencies (3), the expected number of correctly classified observations in each industry branch will be

\[ (4) \quad \frac{M_h}{K} M_h = \frac{M_h^2}{K}; \quad h = 1, \ldots, H \]

In all, the expected number of correctly classified observations from the stratified random choice of industry branch amounts to

\[ (5) \quad C = \sum_{h=1}^{H} \frac{M_h^2}{K} \]

By our proportional chance criterion (5) 74.4 out of the 462 observations would be correctly classified if the industry branch were chosen randomly. This is tantamount to 16.1 per cent. As is recalled, the overall discrimination by the combination of the five financial ratios is 48.1 per cent. Even if there is no mechanical significance statistics available for the comparison, it is clear that the discrimination is significant. This is obvious when one considers the fact that the theoretical range for the discrimination index is from zero to a hundred per cent, and that the index is linear by nature.

4. PREDICTION OF INDUSTRY FROM A SINGLE FINANCIAL RATIO

In financial statement analysis the inter-industry comparisons are normally made one financial ratio at a time. Therefore, we tested the ability of each ratio
to predict which industry branch the observed ratio comes from. The coefficients of the five resultant discriminant functions (each with a single explanatory variable) are given in Appendix B. The percentages of the correct predictions by each of the financial ratios are listed in Appendix D. The financial ratios are presented in the order defined by a stepwise discriminant analysis.

As is seen in Appendix D the best discriminator was financial leverage. The firms in the different industry branches thus differed most in terms of their financial leverage. The overall predictive ability of financial leverage was 27.1 per cent compared with 16.1 per cent of the stratified random choice (see previous chapter). Using financial leverage thus significantly improves on random selection, although the discrimination index must be considered low. Again, there are very significant differences in the results for the different industry branches. For example TOL 61 (wholesale trade) industry is discriminated very well whereas e.g. TOL 38 (manufacture of fabricated metal products, machinery and equipment) is not discriminated well.

It is interesting to speculate why a particular financial ratio would differ from branch to branch. Actually, we expected operating leverage (labor intensiveness) to be the best discriminator, which was found not to be the case. This expectation was based on the fact that the official industry classification is founded on the products produced. Different products involve different production technologies, which in turn was expected to be reflected in distinct operating leverages. As it turned out, operating leverage is not significant, since it could not outdo random choice of industry. This result casts further doubt on the premises of the official industry classification in addition to the reservations voiced in SDLL (1986).

As to financial leverage a potential explanation for its role is found in finance theory. It is common to assert that firms in different industries belong to different risk classes, and can thus bear a different relative amount of debt. Although we do not consider this view propounded by financial theory entirely undisputed, it could in part explain our results.

Inventory turnover was another variable having a clearly better predictive power than random choice. In searching for potential reasons this raises the question whether inventory turnover in days might be better linked to the products produced than operating leverage.

Profitability was not a distinctive factor. This lends support to the assertion that the individual features of a firm are more decisive for its success than its branch of industry.

5. CONCLUSIONS

With the admission that financial ratios are commonly used for intra-industry comparisons, and that this practice is frequently ill-advised because of the heter-
ogeneity of the industry branches with respect to financial ratios, there arises two consecutive problems which constituted the objectives of the present study: 1) What is the magnitude of the risk of biased information from undertaking the said comparisons, and 2) what can be inferred about the nature of the criteria which lie behind the present (official) industry branch classifications. These objectives can be attained by tackling the problem of our study: How reliably is a firm’s industry branch predicted (predefined) by financial ratios.

We used discriminant analysis as our method. The stronger the predictive ability of a financial ratio to discriminate an industry branch, the more homogeneous the industry branch with respect to the financial ratio, and the less risk of making comparisons within an imaginary coherent group. We put forward an index of the predictive ability as a measure of the risk.

In going through the results for individual financial ratios one finds that the variation of the predictive index is large. Indeed, there are incidents where comparisons seem safe. It appears that, generally, the risk is smaller in trade and service industries than in manufacturing industries.

As for the official industry branch classification it seems that it does not have a basis ideally suited for evaluation of firms’ performance. This is inferred from the vast variance of the index of predictive ability both for the financial ratios and the industry branches. The poor performance of labor intensiveness, which comes closest to the nature of the production function, lends further support to our assertion. Summing up, it is probably the criteria of industry classification which ought to be reconsidered rather than the soundness of financial ratios.
APPENDIX A: Features of the Observations

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>N</th>
<th>MEAN</th>
<th>STD DEV</th>
<th>SUM</th>
<th>MINIMUM</th>
<th>MAXIMUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROF</td>
<td>462</td>
<td>0.0979</td>
<td>0.0832</td>
<td>45.2369</td>
<td>-0.1707</td>
<td>0.4409</td>
</tr>
<tr>
<td>LEVE</td>
<td>462</td>
<td>0.6600</td>
<td>0.2346</td>
<td>304.9430</td>
<td>0.1861</td>
<td>1.5436</td>
</tr>
<tr>
<td>LIQV</td>
<td>462</td>
<td>-0.0506</td>
<td>0.4270</td>
<td>-23.4018</td>
<td>-0.7662</td>
<td>5.4378</td>
</tr>
<tr>
<td>INVE</td>
<td>462</td>
<td>166.6818</td>
<td>91.7578</td>
<td>77007.0000</td>
<td>0.0000</td>
<td>606.0000</td>
</tr>
<tr>
<td>PROD</td>
<td>462</td>
<td>0.7688</td>
<td>0.5603</td>
<td>355.2035</td>
<td>-4.0996</td>
<td>4.6462</td>
</tr>
</tbody>
</table>

PEARSON CORRELATION COEFFICIENTS / PROB>|R| UNDER HO: RHO = 0 / N = 462

<table>
<thead>
<tr>
<th></th>
<th>PROF</th>
<th>LEVE</th>
<th>LIQV</th>
<th>INVE</th>
<th>PROD</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROF</td>
<td>1.0000</td>
<td>-0.2156</td>
<td>0.0415</td>
<td>-0.1082</td>
<td>0.2332</td>
</tr>
<tr>
<td>LEVE</td>
<td>-0.2156</td>
<td>1.0000</td>
<td>-0.2618</td>
<td>-0.0211</td>
<td>-0.3571</td>
</tr>
<tr>
<td>LIQV</td>
<td>0.0415</td>
<td>-0.2618</td>
<td>1.0000</td>
<td>-0.2838</td>
<td>-0.0059</td>
</tr>
<tr>
<td>INVE</td>
<td>-0.1082</td>
<td>-0.0211</td>
<td>-0.2838</td>
<td>1.0000</td>
<td>0.0311</td>
</tr>
<tr>
<td>PROD</td>
<td>0.2332</td>
<td>-0.3571</td>
<td>-0.0059</td>
<td>0.0311</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

The figures below the correlation coefficients give the t-test risk levels in testing the hypothesis Ho: R = 0. Thus, using the 5 % risk level, e.g. a hypothesis of the independence of PROF and LEVE would be rejected, while between PROF and LIQV it would not be rejected.

APPENDIX B: Coefficients of Discriminant Functions for Each Branch

DISCRIMINANT ANALYSIS

<table>
<thead>
<tr>
<th></th>
<th>TOL 31</th>
<th>TOL 32</th>
<th>TOL 34</th>
<th>TOL 35</th>
<th>TOL 36</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROF</td>
<td>33.0260</td>
<td>25.5828</td>
<td>29.7573</td>
<td>34.2386</td>
<td>30.7359</td>
</tr>
<tr>
<td>LEVE</td>
<td>48.6778</td>
<td>42.7886</td>
<td>57.1332</td>
<td>44.7591</td>
<td>41.4544</td>
</tr>
<tr>
<td>LIQV</td>
<td>4.2954</td>
<td>4.4351</td>
<td>4.8276</td>
<td>4.1558</td>
<td>3.9661</td>
</tr>
<tr>
<td>INVE</td>
<td>0.0775</td>
<td>0.0761</td>
<td>0.0907</td>
<td>0.0672</td>
<td>0.0651</td>
</tr>
<tr>
<td>PROD</td>
<td>4.8582</td>
<td>6.7073</td>
<td>6.0573</td>
<td>5.4934</td>
<td>4.5936</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>TOL 38</th>
<th>TOL 61</th>
<th>TOL 62</th>
<th>TOL 71</th>
<th>TOL 83</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEVE</td>
<td>45.8538</td>
<td>30.5417</td>
<td>41.4596</td>
<td>69.4511</td>
<td>55.9466</td>
</tr>
<tr>
<td>LIQV</td>
<td>4.3503</td>
<td>4.4879</td>
<td>4.1944</td>
<td>5.3845</td>
<td>5.5165</td>
</tr>
<tr>
<td>INVE</td>
<td>0.0785</td>
<td>0.0409</td>
<td>0.0600</td>
<td>0.0621</td>
<td>0.0698</td>
</tr>
<tr>
<td>PROD</td>
<td>6.7225</td>
<td>4.6922</td>
<td>7.8019</td>
<td>5.6649</td>
<td>6.9208</td>
</tr>
</tbody>
</table>

Model with five financial ratios:

\[
\text{CONSTANT} = -0.5 \bar{X}_j' \text{COV}^{-1} \bar{X}_j
\]

\[
\text{COEFFICIENT VECTOR} = \text{COV}^{-1} \bar{X}_j
\]
Models with a single financial ratio:

<table>
<thead>
<tr>
<th>Ratio</th>
<th>TOL 31</th>
<th>TOL 32</th>
<th>TOL 34</th>
<th>TOL 35</th>
<th>TOL 36</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-0.9770</td>
<td>-0.6592</td>
<td>-0.4514</td>
<td>-1.5385</td>
<td>-1.0718</td>
</tr>
<tr>
<td>PROF</td>
<td>17.2344</td>
<td>14.1574</td>
<td>11.7158</td>
<td>21.6273</td>
<td>18.0514</td>
</tr>
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**APPENDIX C:** Standard Industry Classification TOL and the Firms Included in the Sample

TOL 31 Manufacture of Food, Beverages and Tobacco
   Amer, Huhtamäki, Rettig, Suomen Sokeri
TOL 32 Textile, Wearing Apparel and Leather Industries
   Finlayson, Lassila & Tikanoja, Marimekko, Tamfelt, Suomen Trikoo
TOL 34 Manufacture of Paper and Paper Products, Printing and Publishing
   Enso-Gutzeit, Kajaani, Kaukas, Kemi, Kymi-Strömberg, Metsäliiton Teollisuus, Otava,
   Wilh. Schauman, G.A. Serlachius, Tampella, Werner Söderström, Yhtyneet Paperitehtaat
TOL 35 Manufacture of Chemicals and of Chemical, Petroleum, Coal, Rubber and
   Plastic Products
   Farmos, Medica
TOL 36 Manufacture of Non-metallic Mineral Products, Except Products of Petroleum and
   Coal
Lohja, Partek
TOL 38 Manufacture of Fabricated Metal Products, Machinery and Equipment
Fiskars, Instrumentarium, Kone, Nokia, Rauma-Repola, W. Rosenlew, Wärtsilä
TOL 61 Wholesale Trade
Finvest, Ford, Kesko, Rake, Tamro, Talous-Osakekauppa
TOL 62 Retail Trade
Kuusinen, Stockmann
TOL 71 Transport and Storage
Effoa
TOL 83 Real Estate and Business Services
Tietotehdas

APPENDIX D: Predictive Ability of Individual Financial Ratios

TEYTLEVE (financial leverage)
TOL 31: 12/44 = 27.3 %
TOL 32: 9/55 = 16.4 %
TOL 34: 27/132 = 20.5 %
TOL 35: 2/22 = 9.1 %
TOL 36: 2/22 = 9.1 %
TOL 38: 11/77 = 14.3 %
TOL 61: 47/66 = 71.2 %
TOL 62: 1/22 = 4.5 %
TOL 71: 9/11 = 81.8 %
TOL 83: 5/11 = 45.5 %
Overall: 125/462 = 27.1 %

TEYTINVE (turnover ratios: inventory turnover in days)
TOL 31: 8/44 = 18.2 %
TOL 32: 4/55 = 7.3 %
TOL 34: 54/132 = 40.9 %
TOL 35: 2/22 = 9.1 %
TOL 36: 2/22 = 9.1 %
TOL 38: 3/77 = 3.9 %
TOL 61: 36/66 = 54.5 %
TOL 62: 2/22 = 9.1 %
TOL 71: 11/11 = 100.0 %
TOL 83: 2/11 = 9.1 %
Overall: 124/462 = 26.8 %

TEYTPROD (operation leverage: labor intensiveness)
TOL 31: 11/44 = 25.0 %
TOL 32: 9/55 = 16.4 %
TOL 34: 4/132 = 3.0 %
TOL 35: 1/22 = 4.5 %
TOL 36: 3/22 = 13.6 %
TOL 38: 6/77 = 7.8 %
TOL 61: 9/66 = 13.6 %
TOL 62: 12/22 = 54.5 %
TOL 71: 11/11 = 100.0 %
TOL 83: \( \frac{6}{11} = 54.5\% \)
Overall: \( \frac{72}{462} = 15.6\% \)

TEYTPROF (profitability: return on assets)
TOL 31: \( \frac{2}{44} = 4.5\% \)
TOL 32: \( \frac{0}{55} = 0.0\% \)
TOL 34: \( \frac{22}{132} = 16.7\% \)
TOL 35: \( \frac{11}{22} = 50.0\% \)
TOL 36: \( \frac{1}{22} = 4.5\% \)
TOL 38: \( \frac{3}{77} = 3.9\% \)
TOL 61: \( \frac{1}{66} = 1.5\% \)
TOL 71: \( \frac{8}{11} = 72.7\% \)
TOL 83: \( \frac{0}{11} = 0.0\% \)
Overall: \( \frac{49}{462} = 10.6\% \)

TEYT LIQV (liquidity: quick asset ratio)
TOL 31: \( \frac{4}{44} = 9.1\% \)
TOL 32: \( \frac{1}{55} = 1.8\% \)
TOL 34: \( \frac{66}{132} = 50.0\% \)
TOL 35: \( \frac{2}{22} = 9.1\% \)
TOL 36: \( \frac{1}{22} = 4.5\% \)
TOL 38: \( \frac{1}{77} = 1.3\% \)
TOL 61: \( \frac{9}{66} = 13.6\% \)
TOL 71: \( \frac{0}{11} = 0.0\% \)
TOL 83: \( \frac{9}{11} = 81.8\% \)
Overall: \( \frac{99}{462} = 21.4\% \)

REFERENCES


