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A credit scoring approach for the commercial banking sector

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Abstract

For managing credit risk, commercial banks use various scoring methodologies to evaluate the financial performance of client firms. This paper upgrades the quantitative analysis used in the financial performance modules of state-of-the-art credit scoring methodologies. This innovation should help lending officers in branch levels filter out the poor risk applicants. The Data Envelopment Analysis-based methodology was applied to current data for 82 industrial/manufacturing firms comprising the credit portfolio of one of Turkey's largest commercial banks. Using financial ratios, the DEA synthesizes a firm's overall performance into a single financial efficiency score—the "credibility score". Results were validated by various supporting (regression and discriminant) analyses and, most importantly, by expert judgments based on data or on current knowledge of the firms.

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1. Introduction

The economic and, therefore, the social well-being of developing countries with fairly privatized economies is highly dependent on the behavior of a country's commercial banking sector. Banks provide credit to sustain manufacturing, agricultural, commercial and service enterprises. These, in turn, provide jobs thus enhancing purchasing power, consumption, and savings. Bank failures, especially in such settings, send shockwaves affecting the social fabric of the country as a whole and, as experienced recently, (Latin America and Asia) have the potential of a quick global impact. Thus, it is imperative that lending/credit decisions are made as prudently as possible while keeping the decision making process both efficient and effective.

Commercial banks provide financial products and services to clients while managing a set of multi-dimensional risks associated with liquidity, capital adequacy, credit, interest and foreign

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exchange rates, operating and sovereign risks, etc. In this sense, banks may be considered to be "risk machines". They take risks, and transform or embed such risks to provide products and services [1].

Banks are also "profit-seeking" organizations basically formed to make money for shareholders. In their typical decision-making processes (i.e. pricing, lending, funding, hedging, etc.), they try to optimize their "risk-return" trade-off. Management of risk and of profitability are very closely related. Risk taking is the basic requirement for future profitability. In other words, today's risks may turn up as tomorrow's realities. Therefore, banks may not live without managing these risks.

Among the different banking risks, credit risk has a potential "social" impact because of the number and diversity of stakeholders affected. Business failures affect shareholders, managers, lenders (banks), suppliers, clients, the financial community, government, competitors, and regulatory bodies, among others. In the age of telecommunications, the ripple effect of a bank failure is virtually instantaneous and such ripples hold the potential of global impact. In order to effectively manage the credit risk exposure of a modern bank, there is thus a strong need for sophisticated decision support systems backed by analytical tools to measure, monitor, manage, and control, financial and operational risks and inefficiencies.

Conscious risk-taking decisions call for quantitative risk-management systems, which, in turn, provide the bank early warnings for predicting potential business failures. Thus, an effective risk-monitoring unit supports managers' judgments and, hence, the profitability of the bank. A potential client's credit risk level is often evaluated by the bank's internal credit scoring models. These aim to determine whether an applicant has the capacity to repay by evaluating the credit risk of his loan application. This is normally done using historical data and statistical techniques. Such models offer banks a means for evaluating the risk of their credit portfolio, in a timely manner, by centralizing global-exposures data and by analyzing marginal as well as absolute contributions to risk components. These models can offer useful insight and do provide an important body of information to help a bank formulate its risk management strategies. Models that are conceptually sound, empirically validated, backed by good historical data, understood and implemented by management, augment the business success of credit quality.

Over the past decade, several financial crises observed in some emerging markets enjoying a recent financial liberalization experience, showed that debt financing built on capital inflow may result in large and sudden capital outflows, thereby causing a domestic "credit crunch". A glance into the causes of these financial crises indicates that credit expansion funded mainly by capital inflows leads to over investment and renders banks and the corporate sector vulnerable to shocks. Experience with these recent crises forced banking authorities, i.e. the Bank of International Settlements (BIS), the World Bank, the IMF, as well as the Federal Reserve, to draw a number of lessons. Hence, they all encourage commercial banks to develop internal models to better quantify financial risks. The Basel Committee on Banking Supervision [2], English and Nelson [3], the Federal Reserve System Task Force on Internal Credit Risk Models [4], Lopez and Saidenberg [5] and Treacy and Carey [6] represent some recent documents addressing these issues.

Credit scoring has both financial and non-financial aspects. The scope of the current paper, however, is limited to the evaluation of a bank client's financial performance. Studies attempting to measure firm performance on the basis of qualitative data are exemplified by Bertels et al. [7].

Section 2 of this paper presents a survey of the literature related to the project. Section 3 provides a conceptual framework of the proposed methodology as a series of several (interrelated) analytical methods, while Section 4 discusses validation tests performed on the methodology using recent data from 82 industrial/manufacturing firms. Section 5 argues the relative advantages and the managerial implications of the proposed methodology.

2. Literature survey

Formal or mathematical modeling of finance theory began in the late 1950s. The work of Markowitz [8] represents a major milestone. The practice reached its "take-off" stage as a sub-discipline of Finance during the early 1960s. Some of the early efforts were directed at evaluating a firm for purposes of mergers and acquisitions [9]; some dealt with using investment portfolios to manage risk [10]; others dealt with improvement/optimization of a firm's financing mix [11]. They were all directed at enhancing extant finance theory toward the goal of guiding decision-makers.

One of the fields in which formal or mathematical modeling of finance theory has found widespread application is risk measurement. A firm's financial information plays a vital role in decision making of risk-taking activities by different parties in the economy. An extensive literature dedicated to the prediction of business failure as well as credit scoring concepts has emerged in recent years [12–15]. Financial ratios are the simplest tools for evaluating and predicting the financial performance of firms. They have been used in the literature for many decades.

The benefits and limitations of financial ratio analysis are addressed in a widely used text on managerial finance [16]. Financial statements report both on a firm's position at a point in time and on its operations over some past period. However, there are still some limitations in using ratio analysis: (i) many large firms operate in a number of different industries. In such cases it is difficult to develop a meaningful set of industry averages for comparative purposes; (ii) inflation badly distorts a firm's balance sheet. Moreover, recorded values are often substantially different from their "true" values; (iii) seasonal factors can distort a ratio analysis; (iv) firms can employ "window dressing techniques" to make their financial statements look stronger; (v) it is difficult to generalize about whether a particular ratio is "good" or "bad"[1]; and (vi) a firm may have some ratios looking "good" and others looking "bad" making it difficult to tell whether the firm is, on balance, strong or weak.

Across different countries, sectors and/or periods of time, financial ratios that have been found useful in predicting failure differ from study to study [15].

To deal with the above shortcomings of unidimensional financial ratio analysis, a variety of methods have appeared in the literature for modeling the business failure prediction process. An excellent comprehensive literature survey can be found in Dimitras et al. [15].

In the late 1960s, discriminant analysis (DA) was introduced to create a composite empirical indicator of financial ratios. Using financial ratios, Beaver [13] developed an indicator that best differentiated between failed and non-failed firms using univariate analysis techniques. The

[1] For example, a high current ratio may indicate a strong liquidity position, which is good, or excessive cash which is bad (because excess cash is a non-earning asset). Hence, interpretation of the ratio is context-dependent.

univariate approach was later improved and extended to multivariate analysis by Altman [12]. Altman established that ratios found not to be very significant by univariate models, could prove somewhat useful in a discriminant function which considers the relationships among variables. Hence, he considered several variables simultaneously using multiple discriminant analysis (MDA). He argued that MDA had the advantage of considering an entire profile of interrelated characteristics common to the relevant firms. That study also aimed to predict future failure on the basis of financial ratios. A univariate study, on the other hand, considers the measurements used for group assignments one at a time only. In choosing the variables for use within the discriminant function, Altman examined the statistical significance of various alternative functions, interrelations between the relevant variables, predictive accuracy of various profiles and his own judgment. He concluded that his bankruptcy prediction model was an accurate forecaster of failure for up to 2 years prior to bankruptcy and that the model's accuracy diminishes substantially as the lead-time increases. In spite of widespread use of MDA, Altman [12, p. 601], confesses to the following weakness of discriminant analysis:

> Up to this point the sample firms were chosen either by their bankruptcy status (Group 1) or by their similarity to Group 1 in all aspects except their economic well being. But what of the many firms which suffer temporary profitability difficulties, but in actuality do not become bankrupt.

During the years that followed, many researchers attempted to increase the success of MDA in predicting business failure [15]. Among these are Eisenbeis [17]; Peel et al. [18]; and Falbo [19]. Such work also involved Turkish firms. Examples are Unal [20], and Ganamukkala and Karan [21].

Linear probability and multivariate conditional probability models (Logit and Probit) were introduced to the business failure prediction literature in late 1970s. The contribution of these methods was in estimating the probability of a firm's failure. The linear probability model is a special case of ordinary least-squares regression with a dichotomous dependent variable [15].

In the 1980s, studies utilizing the recursive partitioning algorithm (RPA) based on a binary classification tree rationale were applied to this problem by Frydman et al. [22] and Srinivasan and Kim [23].

In the 1980s and 1990s, the use of several mathematical programming techniques enriched the literature. The basic goals of these methods were to escape the assumptions and restrictions of previous techniques and to improve classification accuracy.

In the early 1990s, decision support systems (DSS) in conjunction with the paradigm of multi-criteria decision-making (MCDM), were introduced to financial classification problems. Zopounidis [24], Mareschal and Brans [25], Zopounidis et al. [26], Diakoulaki et al. [27], Siskos et al. [28] and Zopounidis and Doumpos [29] were among the studies that measured firm performance aiming at predicting business failure by making use of DSS and MCDM. The ELECTRE method of Roy [30] and the Rough Sets Method of Dimitras et al. [14] represent studies addressing these issues. Development and application of artificial intelligence resulted in the use of expert systems [23,31–33]. Neural Network methods were applied to the bankruptcy problem as well [34].

In the late 1990s, data envelopment analysis (DEA) was introduced to the analysis of credit scoring as in Troutt et al. [35], Simak [36], and Cielen and Vanhoof [37]. As opposed to the broadly known MDA approach for business failure prediction (which requires extra a priori information, i.e. good/bad classification), DEA requires solely ex-post information, i.e. the observed set of inputs and outputs, to calculate the credit scores. Thus, it opened new horizons for credit scoring.

DEA, widely known as a non-parametric approach, is basically a mathematical programming technique developed by Charnes, Cooper and Rhodes (CCR) [38] to evaluate the relative efficiency of "decision making units" (DMUs). DEA converts a multiplicity of input and output measures into a unit-free single performance index formed as a ratio of aggregated output to aggregated input. A productivity maximization rationale is elegantly embedded in its original fractional formulation. The capability of dealing with multi-input/multi-output settings provides DEA an edge over other analytical tools. Conceptually, DEA compares the DMUs' observed outputs and inputs in order to identify the relative "best practices" for a chosen observation set. Based on these best observations, an efficient frontier is established and the degree of efficiency of other units with respect to the efficient frontier is then measured. Based on its input-oriented DEA formulation, the resulting performance index value (the credibility score, in our context) provides a numerical value E. E lies between zero and one. If E is less than one, the DMU is considered "inefficient" as compared to the efficient frontier derived from best practices. If E is equal to one, the DMU is located on the efficient frontier. Therefore, it can be said that E measures the relative credit riskiness of firms within the bank portfolio.

Yeh [39], was one of the first researchers to combine DEA with financial ratio analysis. She utilized DEA to evaluate bank performance. Her study empirically demonstrated that DEA, in conjunction with financial ratio analysis, can effectively aggregate and reclassify the perplexing ratios into meaningful financial dimensions, which enable analysts to gain insight into the financial operating strategies of banks. Yeh [39, pp. 980–981] explains the merit of DEA as follows:

> A number of studies have attempted to use statistical methods (such as discriminant, Logit and Probit analyses) with financial ratios to generate early warning signals for distressed banking institutions… The idea is to develop meaningful "peer group analysis", that is, to develop specific financial characteristics that distinguish between two or more groups, for example, failed and non-failed banks, or problem and non-problem banks, with relatively "good" or "bad" financial conditions. However, except when a priori groups are available to provide certain financial profiles for comparison, identifying appropriate peer group analysis is a difficult task. Data envelopment analysis (DEA), which computes a firm's efficiency by transforming inputs into outputs relative to its peers, may provide a fine mechanism for deriving appropriate categories for this purpose... An advantage of DEA is that, it uses actual sample data to derive the efficiency frontier against which each unit in the sample is evaluated with no a priori information regarding which inputs and outputs are most important in the evaluation procedure. Instead, the efficient frontier is generated, when a mathematical algorithm is used to calculate the DEA efficiency score for each unit.

Although DEA was introduced in the early 1980s, its applications are acquiring more widespread recognition in the financial literature as time passes.

3. The proposed methodology

The proposed methodology consists of seven steps, as outlined in Fig. 1. The first three steps deal with selection of firms for the study and with identification of indicators that may be used to evaluate the firms' financial performance. Steps 4 and 5 determine the financial indicators to be used in DEA to obtain credibility scores of the firms in Step 6. Step 7 validates the DEA credibility scores against those obtained via regression, discriminant, and judgmental analyses.

Step-1: Selecting the observation set. The firms selected may either be those for which credit limits are already allocated by the bank or those that apply for new credit allocation. At this stage,

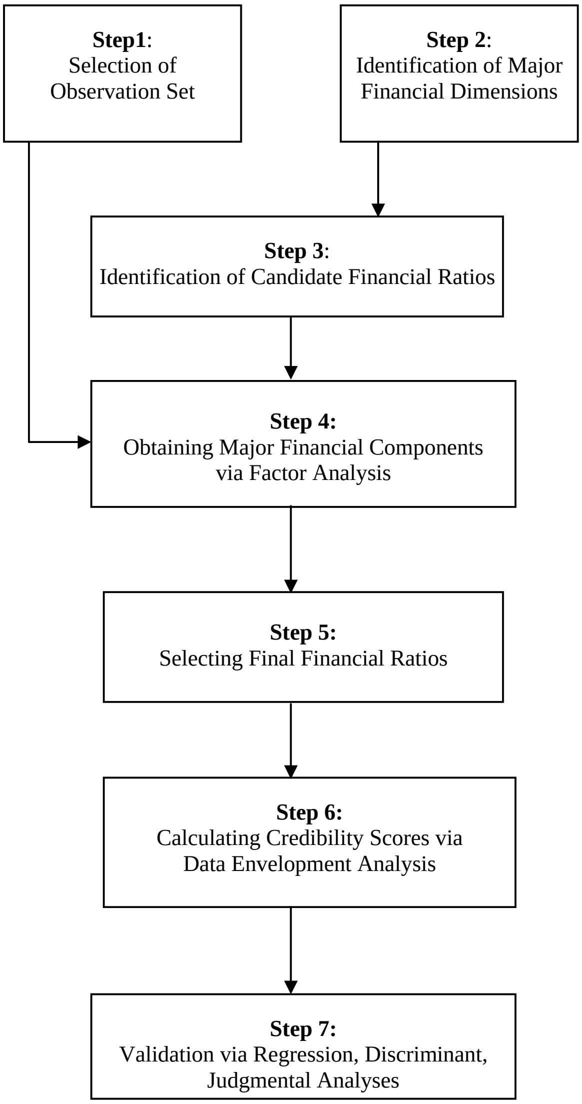


Fig. 1. Flowchart of the approach used.

a certain degree of "homogeneity" in terms of sectoral differences and scale-size is needed among the firms considered. However, it must be recognized that due to operating conditions in the different sectors, financial statement structures of the firms may differ from one sector to another. For example, reporting of the financial results by industrial/manufacturing firms may differ in format from those in tourism or construction. Additionally, seasonality of a sector-specific product may lead to differences in the structure of financial statements.

Step-2: Determining major financial dimensions. As indicated earlier, credit scoring has both financial and non-financial aspects. The dimensions that are analyzed in credit scoring are categorized under five main headings. These are: (i) Capacity (ability to repay); (ii) Character (willingness to repay); (iii) Capital (wealth of borrower); (iv) Collateral (security if necessary); and (v) Conditions (external and economic). These famous five (C) categories of credit management establish the likelihood that a potential or existing borrower will successfully meet scheduled interest and principal payments [40].

As indicated earlier, this study is limited to financial analysis, i.e. it concentrates on the capacity and capital portions of the above categorization. While this does not mean that analysis of non-financial factors is less important, examination of qualitative variables requires different statistical tools.

Traditional financial ratio analysis does not allow for an objective gathering of independent evaluations into a single performance score. The literature on financial ratio analysis is voluminous. It deals with dimensions that have to be considered and individual financial ratios that have to be analyzed. The most common dimensions analyzed are: (i) Liquidity, (ii) Activity, (iii) Financial Structure, (iv) Profitability, (v) Growth, and (vi) Funds Flow Aspects.

Step-3: Determining major financial ratios. In order to cover these dimensions, a broad set of financial ratios needs to be computed. Some ratios in this set may be similar to each other in terms of underlying financial meanings or in terms of mathematical properties. To uncover any relationships, a factor (principal component) analysis is carried out in Step 4.

Step-4: Filtering financial dimensions and obtaining major components via factor analysis. In this step, factor analysis aims at reducing a data set by grouping similar variables. It addresses the problem of analyzing the interrelationships among a large number of variables and then explaining these variables in terms of their common underlying dimensions (factors). The separate dimensions being measured can thus be identified. Financial ratios belonging to the same factor can be assumed to be measures of a similar dimension of the firm. This analysis provides clues for deciding which ratios should be included in the scoring algorithm so as to prevent multicolinearity among variables. It also allows financial analysts to consider as many different financial dimensions of the firm as is possible, and hence perform a meaningful "multi" dimensional analysis. At this stage, some of the ratios are discarded because they are perfectly correlated with other ratios. Alternately stated, given the existence and utilization within the analysis of ratio i, if another ratio j does not add to the explanatory power of the model created then this ratio is excluded from further usage. Moreover, some ratios are excluded in order to satisfy the statistical requirements of factor analysis [41].

Step-5: Selecting final financial indicators via expert opinion in the light of principal components. As discussed earlier, the final selection of financial indicators is based on the factor analysis and expert opinion as well as on hints from the ratio analysis literature. Thus, it is assured that the resulting set of indicators contains the most relevant financial classification dimensions while recognizing the mathematical relationships among the ratios.

Step-6: Calculating firm credibility scores via data envelopment analysis. In DEA, physical or monetary magnitudes are typically used as the input/output set. However, to eliminate scale-size effects in this study, financial ratios were used instead. The resulting DEA score is a relative ratio of two combined linear ratios. This study, however, took advantage of the multi-criteria ranking feature of DEA—a feature based on selection of the relatively best practices within the observation set, and on the radial distance from the efficient frontier comprising these best practices. (See Charnes et al. [38] and Oral and Yolalan [42] for a more in-depth discussion of the DEA model and its applications to the banking industry.)

Step-7: Validation via regression, discriminant, and judgmental analyses. The purpose of this step is to establish the extent to which DEA results coincide with those of regression, discriminant, and judgmental analyses.

(a) *Regression analysis (RA):* In some cases, due to data anomalies, DEA may not sufficiently discriminate firms' efficiencies [43]. There is thus a need to test the explanatory power of the indicator set used in the DEA. Linear regression is suggested as a testing criterion. For this purpose, the DEA scores are taken as the dependent variable, while the financial ratios used in DEA are the independent variables.

(b) *Discriminant analysis (DA):* DA is used to establish the extent to which DEA scores can be used to classify the selected firms into two groups: credit worthy "good" firms and "bad" firms. DA is a statistical technique used to classify an observation into one of at least two a priori established groupings dependent upon the observation's individual characteristics. It is primarily used to classify and/or make predictions of problems where the dependent variable is qualitative. DA then attempts to derive that linear combination of characteristics which discriminates "best" between the two groups [12].

In this study, financial performance—as measured by DEA—is used as the qualitative (i.e. a priori grouping) variable. There are two financial performance groups: The good firms group (GFG) and the bad firms group (BFG). The GFG is defined as those observations with DEA scores over a specific value, whereas the BFG is defined as those observations with DEA scores below that value. As will be discussed later, the "specific value" was chosen by taking into account the distribution of the DEA scores. The financial ratios are used as explanatory variables in the DA. A discriminant function is then generated. The hit ratio (the percentage of right classifications) shows the degree to which DA verifies and validates the classification obtained via DEA.

(c) *Judgmental analysis:* The consistency of the DEA results is also checked against Credit Officers' judgements. The objective is to see to what extent the aggregated expert judgement—based evaluations of the firms coincide with the DEA results. A high ratio of hits indicates that the two sets are in conformity.

4. The application

Below is a description of the application of the methodology to a set of real world commercial bank data.

Step-1: Selecting the observation set. There are indeed studies showing statistically significant differences—from sector to sector—*among* industrial firms in terms of their financial statement structure. For purposes of this study, however, it was decided to obtain data resident in a large private commercial bank's credit department portfolio of industrial/ manufacturing firms. The included firms operate predominantly in sectors such as forestry products, leather, electrical devices, food, paper products, chemicals, machinery, metal, non-metal, plastics, textiles and transportation.

At the beginning of the study, there were approximately 100 firms for which data were available. In order to provide a certain degree of homogeneity among firms in the observation set, however, the outliers, i.e. those firms having several ratios that deviate significantly (more than two standard deviations) from the corresponding mean, were removed. This was done in order to prevent the results from being distorted. The remaining 82[2] "normal" industrial manufacturing firms contributed to healthier, more meaningful study results.[3]

Step-2: Identification of major financial dimensions. Commonly accepted financial dimensions such as Liquidity, Activity, Financial Structure, Profitability, Growth, and Funds Flow Aspects are taken into consideration as guides to identifying potential or candidate financial ratios to be used in the study.

Step-3: Identification of candidate financial ratios. The bank's loan officers' experience-based insight was used to cover a firm's financial structure multidimensionality. This resulted in 46 ratios (see Appendix A). The desired proportion between the number of observations and the number of variables in the factor analysis restricted the number of ratios to 46, although a larger number could have been considered [41].

Step-4: Filtering candidate financial ratios to obtain major financial components. The above broad financial ratio set was next used as input to a factor analysis. The aims were twofold:

(a) To observe the underlying relations and correlations among these ratios, and
(b) To select ratios for use in the financial performance evaluation so as to cover all previously identified major financial dimensions.

Factors were extracted using the method of principal components (those with eigenvalues greater than 1). No constraint was imposed on the number of factors. Rotation of factors was carried out via the orthogonal varimax method. As indicated earlier, some of the 46 ratios were discarded; some because of being perfectly correlated with another ratio, and some in order to satisfy the requirements of the factor analysis [41]. Hence, 4 ratios were left out of the analysis, leaving 42 ratios in the set. These 42 ratios were grouped into 11 factors (see Appendix A).

In terms of common characteristics among the ratios, seven reflect factor-specific character. In other words, in these factors, ratios which are known to reflect similar characteristics in terms of financial dimensions, seem to exhibit a similar feature mathematically as well. These seven factors

[2] The authors recognize that the predictive reliability of any statistically based model can be improved by increasing the size and representativeness of the sample used. However, 82 observations suffice for illustrative purposes. Moreover, reality dictated the size of this set.

[3] These firms have been categorized as good firms or bad firms by credit experts' opinions who took into account both financial and non-financial features.

are: Bank Loans, Fixed Assets, Profitability, Leverage, Liability Term Structure, Liquidity, and Sales and Costs. The rest reflect miscellaneous financial characteristics (see Appendix A).

Step-5: Selecting final financial ratios through expert opinion in light of principal components. In light of the factor analysis results, credit department officers' views, insights from the literature and the authors' best judgments, the following set of financial ratios was selected for use in the study.

The inputs to be minimized are *STBL/CL, CL/NS* and *ABS*, as defined below:

Short term bank loans/current liabilities (STBL/CL). This ratio indicates the share of short-term bank loans in total short-term liabilities. In a sense, it also shows the credit worthiness of a firm. The closer this indicator is to zero the better, since it also indicates riskiness. This may seem counter-intuitive. Consider a country such as Turkey, which is experiencing high public deficit and a high inflation. These conditions can lead to crowding-out effects and to high volatility in the financial markets. In the above context, a firm that is highly dependent on short term bank loans is in a precarious position. If banks fall into liquidity problems, experience a crisis, or shift their portfolios toward a higher share of securities among current assets at the expense of loans, then client-firms unable to rotate or revolve their loans may encounter serious working-capital problems. If, on the other hand, a manufacturing firm relies more heavily on trade credits instead of bank loans, such risks will not be confronted. It should be kept in mind that in a different macro-economic environment where this ratio is accepted as a credibility indicator, the ratio can be understood as an output to be maximized. Hence, minimizing this ratio is not a general rule.

Current liabilities/net sales (CL/NS). This ratio shows the ability of a firm to generate revenues and repay its short-term debt. Since a larger denominator is preferred, the lower this ratio the better.

ABS = |*1–(Fixed assets/owners' equity)*|. It is a desired feature that fixed assets of a client-firm should balance its capital base. If banks finance fixed assets with liabilities, especially current liabilities (since fixed assets will not bring revenues to the bank, at least in the short run), the client will have problems in paying back the credit. This will also lead to cash flow problems for the bank. Hence, the ratio of fixed assets to capital base should be close to one. As this ratio moves away from unity (1) in either direction, an imbalance is indicated. The absolute value of this difference is taken at the minimum as a criterion in the analysis.[4]

The outputs to be maximized are *LR, OE/TA* and *NP/TA,* as defined below:

LR=Liquidity ratio=(current assets—inventories)/current liabilities. This is an indicator of the client's liquidity. The more liquid the firm, the easier it can pay its current obligations. Therefore, the higher this ratio, the better.

OE/TA=Owners' equity/total assets. This ratio is an indicator of the capital adequacy of the firm. The more a firm finances itself with its own resources, the less risky it is for the bank. The higher this ratio, the better.

NP/TA=Net profit/total assets. This ratio is an indicator of the return on total money invested in the firm. The higher a firm's return on its investment, the more cash it generates for paying back

[4] The ABS ratio is so named because it is the absolute value of the distance from 1 (unity) of the *Fixed Assets/Owners' Equity* ratio. We use this ratio to strike a balance between fixed assets (which are long term assets) and owners' equity (which are long term liabilities). Too great a deviation, in either direction, is not desired.

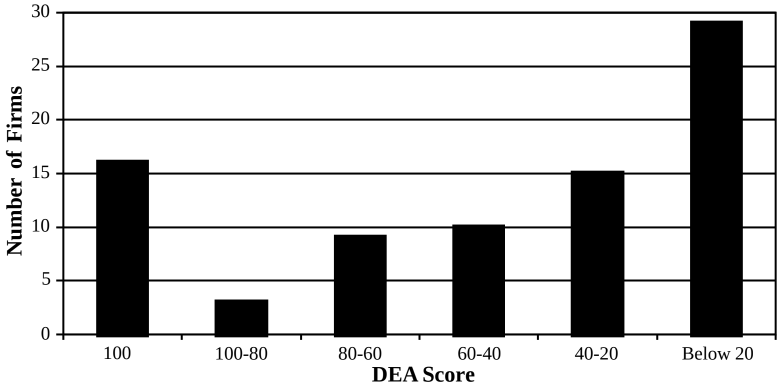


Fig. 2. Distribution of the DEA scores for the 82 sampled firms.

its debt. While the profitability of a certain client is not a unique criterion, it should be taken into account. The higher the profitability, the better.[5]

Step-6: Calculating credibility scores via data envelopment analysis. DEA requires a classification of criteria into two distinct groups, the input and output sets. In this study, *STBL/CL, ABS, CL/NS* are inputs while *NP/TA, OE/TA, LR* are outputs. Here, the DEA algorithm was run and the financial performance scores of client-firms were computed. The credit scores were calculated using the CCR [38] input-oriented DEA model assuming constant returns to scale. In this application, DEA scores were given as percentage points. Hence, the range of scores in the original model, i.e. 0–1, will be reported as 0–100.

The resulting DEA credibility scores vary between 100 and 2.72. Firms with a DEA score of 100 are considered best firms and are said to fall on DEA's "efficient frontier". Fig. 2 shows the distribution of the DEA scores for the 82 sampled firms.

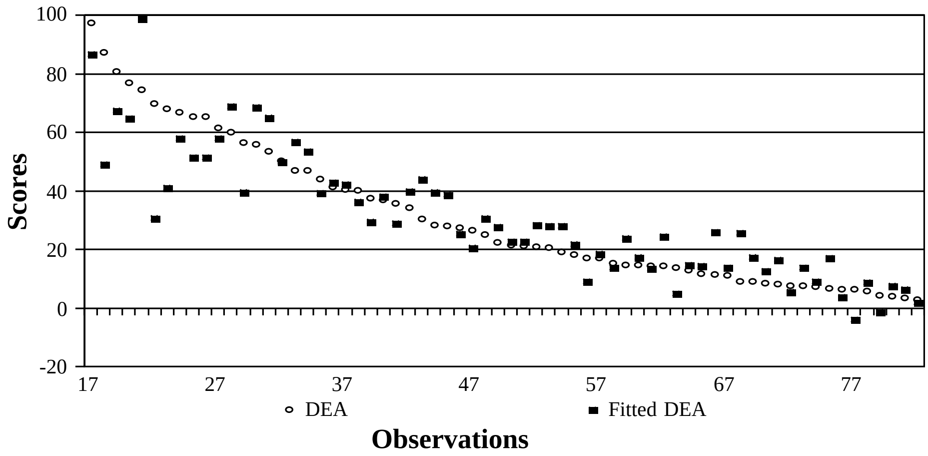
As can be seen in Fig. 2, there are 16 firms with DEA scores of 100. As the DEA score of a firm drops, its financial performance is considered to be relatively worse relative to the other firms in the observation set. It is thus considered to be closer to a probable bad risk in the context of the loan extension process.

Step-7: Validation using regression, discriminant, and judgmental analyses:

(a) *Regression analysis:* In this step, the DEA credibility scores represent the dependent variable, while the six ratios used are considered independent variables. Since DEA cannot discriminate amongst the efficiencies of the "best observations" (firms with a DEA score of 100), the regression was run excluding those observations.[6] Thus, the number of firms used in the

[5] Since the DEA algorithm cannot use negative values, for firms with negative return on assets, this ratio was taken as zero. One can argue that the data can be transformed so that: $NP/TA^* = NP/TA + x$, where x is a positive number defined so that $NP/TA^* \geqslant 0$ for all firms. However, this would only slightly alter the DEA scores without making a significant change in the firms' rankings. Since the aim of this paper is just to show the application of the approach on empirical data, we see no problem in taking negative profitability ratios as zero.

[6] When the regression analysis was run on all observations in the given set of firms, the crucial discrepancy between the original vs. the fitted DEA scores seemed to occur in the region of DEA = 100%. This is not surprising since the



* Observations with a DEA score of 100 are excluded.

Fig. 3. Original vs. fitted DEA scores.

regression was 66. The significance corresponding to the resulting F statistic (4.9×10^{-18}) indicated strong explanatory power of the regression (R^2 78.7%). All variables had expected directions and, with one exception, (net profit/total assets), were statistically significant at the $\alpha = 5\%$ level. These results suggest that the DEA algorithm successfully accounted for five of the six ratios at a statistically significant level. It is interesting to note that the constant term of the regression was also statistically significant.

Eq. (1) represents the regression relationship. This can be seen as a linear approximation of the DEA results. Incidentally, if the observation set is statistically large enough, the regression equation may also be used to rank or to evaluate a new credit applicant without having to run all other steps. In other words, by using the equivalent of (Eq. 1), it is possible to compute the linear approximation of its DEA score without having to run the DEA algorithm each time a new observation is added.

$$\begin{aligned} \mathrm{DEA} = {} & 25 + 23.2\ \mathrm{LR} - 20.3\ \mathrm{CL/NS} - 22.4\ \mathrm{STBL/CL} \\ & + 36.3\ \mathrm{NP/TA} + 47.7\ \mathrm{OE/TA} - 2.4\ \mathrm{ABS}. \end{aligned} \tag{1}$$

Using the regression equation, "fitted DEA scores" were computed and compared with those obtained via DEA in a graph (for the observations which were not on the efficient frontier). See Fig. 3. The actual and fitted values did not differ significantly.

(*footnote continued*)
algorithm cannot discriminate successfully between observations having scores of 100%, i.e. those lying on the efficient frontier. A regression excluding the best observations was thus run to derive a linear approximation of the DEA scores. However, we also ran another regression by including the observations on the efficient frontier. The results were more or less the same, the only difference being the high dispersion among actual and fitted DEA scores for those firms on the efficient frontier. Hence, deriving a regression equation excluding the observations on the efficient frontier seemed reasonable.

Table 1
Groupings of sampled firms

Actual situation	No. of cases	DA "Bad" group	DA "Good" group
Actual "Bad" group	41	38 (92.7%)	3 (7.3%)
Actual "Good" group	41	4 (9.8%)	37 (90.2%)

(b) *Discriminant analysis:* An attempt was made to approximate the DEA results through DA. The firms were classified into two groups with respect to their DEA scores. The "cut-off" point between good and bad firms was selected in an ex-post subjective manner, giving due consideration to the distribution of the DEA scores. Thus, based on the Credit Department judgment that 41 of the firms should be classified as good, those with highest DEA scores were so classified[7], while the remaining ones were classified as bad. Next, DA was run using the above classification as the category variable and the six ratios used as the independent variables. The DA generated a discriminant function with five of the six ratios included (only NP/TA being excluded). As seen from Table 1, DA resulted in a (38 + 37)/(41 + 41) or 91.5% hit ratio.

Eq. (2) represents the resulting unstandardized canonical discriminant function:

$$Z = -0.8 + 0.3\ \mathrm{ABS} + 3.1\ \mathrm{STBL/CL} + 1.7\ \mathrm{CL/NS} - 1.2\ \mathrm{LR} - 1.6\ \mathrm{OE/TA}. \quad (2)$$

As is shown in Fig. 4 the DA-obtained ranking did not differ significantly from that obtained by DEA. This showed that the rating achieved by DEA can indeed be linearly approximated by DA, a somewhat more common technique.

Table 1 shows that the two methods comply with each other in terms of the "Good" and "Bad" classification dichotomy, hence, a high hit ratio. Moreover, Fig. 4 shows that the aggregate DA rankings follow the trend set by DEA. Yet, the firm having the highest DEA score (DEA rank 1) had a DA rank of 51. This is an example where results of the two methods differ significantly at the micro level.[8] Such disparate rankings can be observed in a number of other cases. While these differences in ranking are quite significant, the number of such cases is small. These, we contend, are the "outliers".

The ratio related to profitability, namely [Net Profit/Total Assets], is the one and only ratio—among the six used in DEA—which is both statistically insignificant in the RA and is not included in the discriminant function. This profitability ratio is thus not a criterion in "discriminating" good firms from bad ones, i.e. we cannot say that a firm is "good" if it is profitable or it is "bad" if

[7] The reason for choosing the cut-off point so that 41 firms were grouped as *good* and 41 as *bad*, was to enable comparison of DEA classifications with those of judgmental analysis. As will be explained in the following section, among the 82 firms, credit officers classified 41 as *good* and 41 as *bad*. To check the parallelism among the two classifications, we used the number of *good* vs. *bad* firms corresponding to that determined by credit officers. The fact that 41 is half of 82 happens to be a coincidence.

[8] Actually, firms with DEA ranking from 1 to 16, all had DEA scores of 100. Thus, the firms with ranking from 1st place to 16th, all have equal efficiency levels. Consequently, the firm with DEA rank of 1 is indistinguishable from that with DEA a rank of 16 (same applies to all 16 firms). Thus, the difference between DEA and discriminant rankings for this specific observation can be diminished.

it is marginally, or not at all, profitable. This finding is counterintuitive. It is likely an interesting Turkey-specific feature. At the least, it reflects the database used. Following the Asian crisis in 1997 and the Russian crisis in 1998, the economic situation may have been shaped in such a way that the discriminatory (good vs. bad firms) power of *profitability* may have declined.

Firms that are not currently profitable may nevertheless be fundamentally credit-worthy. It should also be kept in mind that this is a multi-ratio environment, and profitability may not add much to the explanatory power of already existing financial ratios. Credit-worthiness is thus not dependent on any one criterion, but on a multiplicity of criteria. In an environment where market efficiency is higher, *profitability* will surely have more significant explanatory power.

(c) *Judgmental analysis:* Consistency of the DEA results and the views of seasoned credit officer was also checked. As indicated, the bank's loan department rated all firms in the observation set. The hit ratio between the two classifications was 78%. Table 2 shows the degree of parallelism between the two classifications.

Fig. 5 and Table 2 show that, to a certain degree, DEA results are not far from expert opinions. This is an important point because DEA does not consider a priori information. It takes financial aspects into consideration while the judgmental analysis is a mixture of ex-post information consisting of financial and non-financial issues.

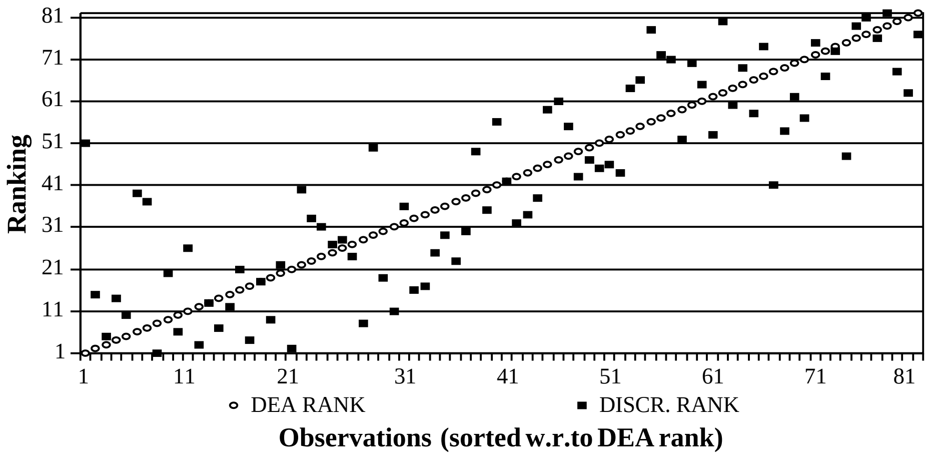


Fig. 4. DEA vs. DA rankings of sampled firms.

Table 2
Comparison of objective (DEA) and subjective classification

	No. of cases	Judgmental good	Judgmental bad
DEA Good	41	32 (78%)	9 (22%)
DEA Bad	41	9 (22%)	32 (78%)

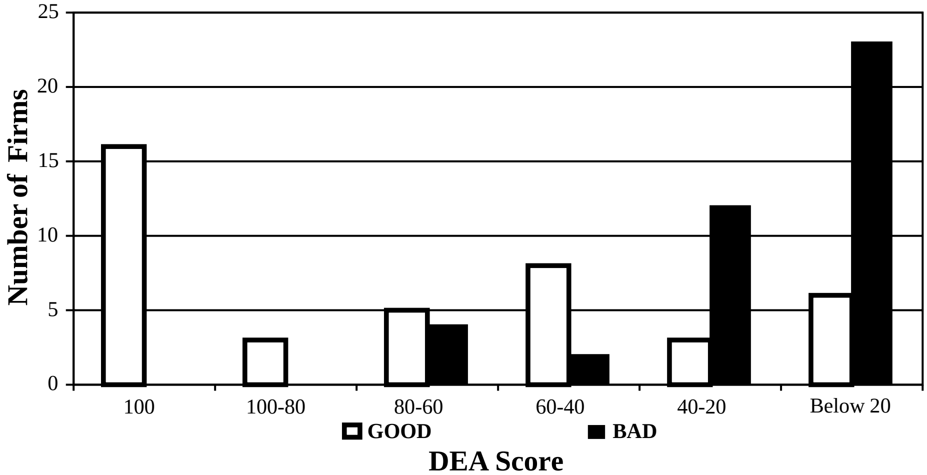


Fig. 5. DEA based classification vs. judgmental analysis.

5. Illustrative example

The following analysis was performed to further interpret the meaning of a low vs. high DEA score at the level of the firm:

The 16 firms falling on the efficient frontier had their respective averages computed for each of the 46 ratios. The same was done for the worst 16 firms, i.e. the 16 firms having the lowest DEA scores. DEA scores of these firms ranged from 2.7% to 11%.

From these averages, *t*-statistics were computed for each of the 46 ratios (see Appendix B).

As might have been expected, results suggest the following:

(i) Short-term bank-loan usage is inversely related to financial efficiency.
(ii) Leverage is lower, or otherwise stated, capital adequacy is higher in better firms.
(iii) Better firms are more liquid.
(iv) Better firms are more profitable.

These findings have great relevance to risks undertaken by the bank. For example, high leverage increases exposure to interest-rate risk. Low liquidity can create liquidity risk. Low profitability, on the other hand, means the fundamental goals of the firm will likely not be achieved.

Thus, the efficiency scores are in line with common sense. Moreover, results show that higher DEA scores point out "better" firms in terms of generally accepted financial dimensions such as liquidity, capital adequacy, and profitability.

6. Concluding remarks

This paper presents a new methodology for measuring the financial performance of firms for purposes of scoring credit worthiness. It involves a multi-dimensional financial ratio analysis, embedded in a credit-scoring algorithm. It includes a chain of analytical methods, relying on DEA, while involving factor analysis, and, for purposes of validation, employs both RA and DA. DEA is used to measure the relative financial efficiency of a given firm in a set of firms. Financial ratios computed from each firm's financial statements were used to obtain a multiple-criteria financial analysis integrating the overall performance of each firm into a single financial efficiency, or "credibility" score. Factor analysis, expert opinion, and results of literature survey were utilized in selecting the financial ratios used in the DEA. The discriminatory power of the DEA algorithm was tested against the results of judgmental, regression, and discriminant analyses. Results suggest that DEA offers a new item in the tool bag of methods for measuring the credit worthiness of firms. Overall, DEA ratings and rankings were parallel to results obtained from discriminant analysis and from the judgments of experts. Regression analysis showed that, in addition to the overall explanatory power of DEA, all but one of the financial ratios used had significant explanatory power on scores reflecting a multi-dimensional measure of financial efficiency.

There are several commercially available Decision Support Systems tailored for credit scoring of commercial and/or industrial firms. At least one is used by commercial banks worldwide. Because of their proprietary nature, not much can be said about the methodologies in these systems. However, for the quantitative aspects of evaluating firms' finances, they rely on statistical methods such as regression and discriminant analyses. As we have shown, DEA and discriminant analysis studies of the same data set generated similar results. In terms of measures of central tendency, they followed the same patterns. However, at the micro or individual firm level, results may differ. Because of the ex-ante vs. ex-post difference, it is suggested that DEA be investigated further for possible augmentation and/or replacement of other methods in the credit scoring methodologies invoked by the commercial bank sector.

In terms of managerial implications, the methodology gives clear insights as to how "bad" firms can improve their financial efficiency. Specifically, "good" firms have higher liquidity, lower bank loans, higher capital adequacy and better balance between their equity and fixed assets.

In order to cover the customer base of a given commercial bank, firms from different sectors were included in the observation set. While it is known that there are some sectoral differences among firms, for the sake of developing a healthier model, the observation set can be limited to a specific sector. However, in such a study the chance of comparing the credibility of firms from different sectors will have been lost.

Lastly, in addition to helping bank executives make decisions as to which clients shall be extended credit and which are to be denied, ipso-facto this methodology allows the commercial bank to monitor, on an ongoing basis, the exposure of its credit portfolio. It is yet another bank management tool for making both strategic and tactical decisions. In countries with bank regulatory systems/agencies, this may well prove to be a tool for compliance monitoring and for advisory purposes.

> As a result of very rapid increases in telecommunications and computer-based technologies and products, a dramatic expansion in cross-border financial flows and within countries has emerged. The pace has become truly remarkable. These technology-based developments have so expanded the breadth and depth of markets that governments, even reluctant ones, increasingly have felt they have had little alternative but to deregulate and free up internal credit and financial markets.

In earlier generations information moved slowly, constrained by the primitive state of communications. Financial crises in the 19th century, for example, particularly those associated with the Napoleonic Wars, were often related to military and other events in faraway places. An investor's speculative position could be wiped out by a military setback, and he might even not know about it for days or even weeks, which, from the perspective of central banking today, might be considered bliss.

[As a result, a] disturbance in one market segment or one country is likely to be transmitted far more rapidly throughout the world economy than was evident in previous eras.

Alan Greenspan, Chairman of the Federal Reserve Board [44].

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Appendix A. Candidate financial ratios

The financial structure multidimensionality of a firm is shown in Table 3.

Table 3

Ratio no.	Ratio name	Factor no.
	Factor 1: bank loans	
1	Short term bank loans/net sales	1
2	Total bank loans/net sales	1
3	Short term bank loans/current liabilities	1
4	Short and long term bank loans/total assets	1
5	Financial expenses/net sales	1
6	Domestic sales/net sales	1
7	Exports/net sales	1
8	Total bank loans/total liabilities	1
	Factor 2: fixed assets	
9	Net material fixed assets/owners' equity	2
10	Fixed assets/owners' equity	2
11	Fixed assets/long term liabilities + owners' equity	2
12	ABS ($\vert 1-$(fixed assets/owners' equity)$\vert$)	2
	Factor 3: profitability	
13	Profit before tax/total assets	3
14	Profit before tax/owners' equity	3
15	Profit before tax/net sales	3
16	Operating profit/net sales	3

Table 3 (*continued*)

Ratio no.	Ratio name	Factor no.
17	Net profit after tax/owners' equity	3
18	Net profit after tax/total assets	3
	Factor 4: leverage	
19	Current liabilities/owners' equity	4
20	Short and long term liabilities/owners' equity	4
21	Depreciation ratio[a]	4
22	Current assets/total assets	4
23	Current liabilities/total assets	4
24	Owners' equity/total assets	4
	Factor 5: miscellaneous	
25	Current liabilities/net sales	5
26	Average collection period of trade receivables (days)	5
27	Average payment period of trade payables (days)	5
28	Short term bank and creditor loans/net sales	5
29	Asset turnover	5
	Factor 6: liability term structure	
30	(Current liabilities-CIA[b])/(total liabilities-CIA)	6
31	Current liabilities/total liabilities	6
	Factor 7: liquidity	
32	Liquidity ratio	7
33	Cash ratio	7
	Factor 8: sales and costs	
34	Gross sales/net sales	8
35	Cost of goods sold/net sales	8
	Factor 9: miscellaneous	
36	Current ratio	9
37	Other liabilities/total assets	9
38	Period[c]	9
	Factor 10: miscellaneous	
39	Net working capital turnover rate	10
40	Current liabilities/(owners' equity + long term liabilities)	10
	Factor 11: miscellaneous	
41	Extraordinary income/net sales	11
42	Other receivables/total assets	11
	Ratios discarded in the factor analysis	
43	Inventory turnover period	—
44	Net working capital ratio[d]	—
45	Extraordinary expenses/net sales	—
46	Gross profit margin	—

[a] Material fixed assets−accumulated depreciation/total assets−accumulated depreciation.

[b] Construction income accruals.

[c] Trade receivables collection period + inventory turnover period−trade payables payment period.

[d] Net working capital/(current liabilities less payables to shareholders, participations, affliated companies and construction income accruals).

Appendix B

The financial ratio t-test analysis results are shown in Table 4.

Table 4

Ratio name	Factor no.	t-statistics	Significance
Short term bank loans/net sales	1	−3.5	0.003
Total bank loans/net sales	1	−3.4	0.004
Short term bank loans/current liabilities	1	−2.7	0.013
Short and long term bank loans/total assets	1	−3.6	0.002
Financial expenses/net sales	1	−2.6	0.016
Domestic sales/net sales	1	1.9	0.070
Exports/net sales	1	−1.9	0.066
Total bank loans/total liabilities	1	−2.6	0.015
Net material fixed assets/owners' equity	2	−2.9	0.010
Fixed assets/owners' equity	2	−3.6	0.003
Fixed assets/long term liabilities + owners' equity	2	−2.3	0.038
Abs (|−(fixed assets/owners' equity)|)	2	−3.4	0.004
Profit before tax/total assets	3	3.6	0.001
Profit before tax/owners' equity	3	0.8	0.416
Profit before tax/net sales	3	3.3	0.003
Operating profit/net sales	3	0.6	0.569
Net profit after tax/owners' equity	3	1.7	0.099
Net profit after tax/total assets	3	3.8	0.001
Current liabilities/ owners' equity	4	−3.9	0.001
Short and long term liabilities/ owners' equity	4	−4.2	0.001
Depreciation ratio	4	1.5	0.136
Current assets/total assets	4	−0.1	0.953
Current liabilities/total assets	4	−3.7	0.001
Owners' equity/total assets	4	5.2	0.000
Current liabilities/net sales	5	−4.9	0.000
Average collection period of trade receivables (days)	5	0.0	0.995
Average payment period of trade payables (days)	5	−3.5	0.002
Short term bank and creditor loans/net sales	5	−6.8	0.000
Asset turnover	5	2.0	0.056
(Current liabilities-CIA)/(total liabilities-CIA)	6	0.5	0.595
Current liabilities/total liabilities	6	0.6	0.568
Liquidity ratio	7	4.5	0.000
Cash ratio	7	2.5	0.024
Gross sales/net sales	8	−0.2	0.846
Cost of goods sold/net sales	8	−0.1	0.936
Current ratio	9	3.7	0.001
Other liabilities/total assets	9	−1.3	0.201
Period	9	0.3	0.779
Net working capital turnover rate	10	−0.5	0.656
Current liabilities/(owners' equity + long term liabilities)	10	−2.8	0.012
Extraordinary income/net sales	11	−0.6	0.550
Other receivables/total assets	11	−0.8	0.418
Inventory turnover period		−2.7	0.012
Net working capital ratio		3.7	0.001
Extraordinary expenses/net sales		1.3	0.196
Gross profit margin		0.1	0.936

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