International Review of Business Research Papers
Vol. 14. No. 1. March 2018 Issue. Pp. 54 – 67

An Alternative Proposal based on Organizational Effectiveness and Efficiency Ratios for Forecasting the Financial Status of a Firm

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Assessing the insolvency risk is certainly a central issue for economic and financial analysis and of prime importance to financial intermediaries. Despite that, no agreement yet exists. Institutional factors specific to each country, as well as a large variety of other causes which can lead to the failure of a firm, obstruct the way to a general theory. It is instead necessary to deal with this issue, not only because it is central to credit management by banking operators, but also for its overall impact on the economy. This paper analyzes how to forecast the financial status (non-defaulting/defaulting) of a firm. To this aim, alternative procedures were tested on the same data set. Specifically, after analyzing the adequacy of Altman's Z-score model, (i) it was attempted to solve its well-known limit due to the consideration of the same number of non-defaulting and defaulting firms in the group, (ii) explicative variables related to a firm's risk of bankruptcy were selected, and finally, (iii) an alternative approach based on panel data was used to divide firms in non-defaulting/defaulting sub-groups. In this way, a considerable reduction of errors in the prediction of a firm's financial status was progressively obtained.

JEL Codes: G17, G21, C51, C58.

1. Introduction

Assessing the insolvency risk is certainly a central issue for economic and financial analysis and of prime importance to financial intermediaries. Despite that, no agreement yet exists. Institutional factors peculiar to each country, as well as a large variety of other causes which can lead to the failure of a firm, obstruct the way to a general theory. It is instead necessary to deal with this issue, not only because it is central to credit management by banking operators, but also for its overall impact on the economy (Basel Committee 2006).

Talking about insolvency risk entails talking about Altman's Z-score because it is the point of reference for most credit risk models. For this reason, this study starts with a literature review on the main forecasting models of the financial status of a firm and on the above-mentioned approach, underlining its weakness (Section 2). Then, in Section 3 (on the methodology and model) a set of actions to obtain better results in term of a firm financial status (non-defaulting/defaulting) forecasting will be suggested. Among them, the use of a panel regression analysis may solve some problems of the discriminant analysis (i.e. of the statistical method used by Altman) leading to an improvement in the firm financial status forecasting error. In Section 4 there are the results obtained by the different procedures

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applied to the data set used and their contextualization and relevance evaluation from an organizational point of view. Section 5 concludes.

2. Literature Review

The production of forecasting models of the financial status of a firm has been a central issue since the Second World War. Briefly, the forecasting model is an approach meant to preventatively diagnose the first symptoms of a firm's financial crisis and consequentially allow stakeholders to make informed decisions. Such models can be grouped into qualitative models (which base themselves on the presupposition that an analysis founded merely on numerical values and, in particular, on balance sheet indexes, strongly limits a judgement of merit on the health status of the entity in question) and quantitative models (based only on balance sheet indexes).

The most common qualitative model is the "A score model" (Argenti 1976). According to this approach, management weaknesses and limits of the accounting system (first variable) cause errors (second variable) which lead to default symptoms (third variable). By attributing a grade to each component of these three variables, it is possible to obtain a score (the "A score") which, if less than 25, indicates a heightened probability of insolvency. The forecasting ability of this model has never been scientifically tested, and moreover, it is evident that such a model is based on a widely subjective attribution of scores.

The quantitative models can be grouped in theoretic and empirical models. The first category has never been used in practice because it refers to "ideal" firms and follows an abstract and simplistic logic according to which a liquidation value lower than that of the liabilities inevitably leads to default. On the contrary, the empirical models use an inductive and statistic approach on a representative sample of firms to obtain general rules. There have been many attempts to define empirical models (Beaver 1966; Altman, 1968; Taffler & Tishaw 1977; Bilderbeek 1979; Ohlson 1980; Taffler 1983; Zavgren 1985; Ezzamel, Brodie & Mar-Molinero 1987; Jones 1987; Gilbert, Menon & Schwartz 1990).

Among them, Altman's Z-score has certainly been the most used. Applying a multivariate discriminant analysis to estimate the coefficients of five-selected balance sheet indicators describing the financial and economic status of a firm (liquidity, asset solidity, profitability, financial structure and productivity), Altman (1968, pp. 589-611) assessed in advance the bankruptcy probability of a unit. The Z-score model is defined as follows

$$Z = 0.012X_1 + 0.014X_2 + 0{,}033X_3 + 0.006X_4 + 0.999X_5 \tag{1}$$

where

X_1= Working capital / Total assets;
X_2 = Retained earnings / Total assets;
X_3= EBIT / Total assets;
X_4= Market value of equity / Book value of total debt;
X_5 = Sales / Total assets.

If

a) Z ≤1.8, the bankruptcy probability is extremely high;

b) $1.8 < Z \leq 2.7$, it is quite likely that the firm will become bankrupt;
c) $2.7 < Z \leq 3$, some caution is needed, but it is unlikely that the firm will become bankrupt;
d) $Z > 3$, the firm is unlikely to default.

Altman derived the Z-score coefficients - and the ranges quoted above - considering a sample of 66 manufacturing corporations, equally divided in the two groups of non-bankruptcy/bankruptcy firms.

Using an F-test, Altman concluded that, for classification purposes, the most relevant variables are X_3 (profitability ratio), X_5 (productivity ratio) and X_4 (financial structure ratio). For the year immediately prior to failure, the model proved extremely accurate when it was tested on a sample of firms different from those used to estimate the parameters. Type I error (failure of a firm when bankruptcy was not predicted), the most dangerous, and type II error (non failure of a firm when bankruptcy was predicted) were both modest. Altman later suggested using the same model for privately held companies by modifying the X_4 variable as Net worth / Total debt (Altman 1993).

In his initial work, and in the following analyses, Altman used equally sized subgroups, so that the data set was composed of 50% non-defaulting firms and 50% defaulting ones (we refer to this composition type as “50-50 group” of firms). This choice was dictated by a number of factors including the need to reduce variance in coefficients’ estimation, the need to identify the differences between groups more efficiently and the necessity to contain the costs of selecting the firms to include into the dataset.

In any case, this balance between non-defaulting and defaulting firms contrasts with the concept of random sampling, since it can only be based on *ex post* knowledge of some characteristics of the firm meaning that the forecasting capacity of the model is conditioned in an *ex ante* decision-making context (Mossman et al. 1999). In fact, in theory, the numerousness of the subsets should reflect the actual non-defaulting/defaulting composition of the population (Marconi, Quaranta & Tartufoli 2012). This is the only way in which the estimated model can be applied directly to the real context with probability that coincides *a priori* with the sample without having to make further adjustments.

Moreover, the Altman model considers the parameters estimated by the discriminant function valid, and therefore constant, for long periods. Actually, this aspect is closely connected to the *ex-ante* and *ex-post* predictive capacity of a model. Although maintenance of the diagnostic capability over time is doubtless based on the stability of the relationships observed between the explanatory variables and bankruptcy, it is necessary to periodically verify the model’s performance and perhaps to re-estimate the parameters when the discriminant analysis efficiency tends to be reduced (like national banks suggest) (Peel & Peel 1987; Gordy 2003).

The selection of explanatory variables in Altman’s model is the result of a purely empirical research process with adaptations often dependent on individual choices, and consistent with the basic absence of a solid firm bankruptcy or crisis theory (Gordy 2000; Gilbert, Menon & Schwartz 1990). The problem has therefore been raised of testing whether it is still worth using the same variables in a different space-time context or, rather, whether they are still able to classify a firm efficiently, such as minimizing the type I and type II errors (Johnsen & Melicher 1994; Kealhofer 2003). Altman used a multivariate discriminant analysis to estimate the coefficients of the five balance sheet indicators specifically selected. Actually, also this approach had many criticisms (Eisenbeis 1997; Altman & Sabato 2005)**.** Among

them, in essence, this methodology is based on the strong assumptions i) that the indicator distribution is a multivariate normal one, ii) that the means of the balance sheet indexes of the two groups are significantly different and iii) on the equality of the two groups' variance-covariance matrix.

In recent years, the possibility to forecast the financial status of a firm and other correlated aspects has been treated by many authors. Shumway (Shumway 2001) argued that hazard models are more appropriate than single-period models for forecasting bankruptcy and proposed a model that uses both accounting ratios and market-driven variables to produce out-of-sample forecasts that are more accurate than those of alternative models. Grice and Ingram (Grice & Ingram 2001) examined how Altman's original model was still useful for predicting bankruptcy in the 2000s, in particular in relation to non-manufacturing firms.

Hillegeist, Keating, Cram and Lundstedt (2004, pp. 5–34) assessed whether Altman's Z-Score and Ohlson's O-Score effectively summarize publicly available information on the probability of bankruptcy. In particular, they compared the relative information content of these scores to a market-based measure of the probability of bankruptcy that they developed based on the Black–Scholes–Merton option-pricing model (BSM-Prob).

Altman and Sabato (2007, pp. 332-357) developed a distress prediction model specifically for the SME sector. Altman, Danovi and Falini (2013, pp. 1-10) applied the Z-score model to Italian companies subject to extraordinary administration concluding that the model is applicable to the Italian manufacturing context, with a few cautions. The analysis carried out showed the potential to reformulate the parameters based on the characteristics of Italian companies, namely: low capitalization, heavy use of bank credit and budget policies which at the time were not transparent.

Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2014, pp. 1-47) analyzed the performance of the Altman Z-score model on firms from 34 European and non-European countries showing that the classification accuracy may be considerably improved with country-specific estimation especially with the use of additional variables.

Almamy, Aston and Ngwa (2016, pp. 278-285) investigated the capability of the Z-score model in predicting the health of UK companies. They used discriminant analysis, and performance ratios to test which ratios are statistically significant in predicting the health of UK companies from 2000 to 2013. In conclusion, the authors added a new variable to Altman's original Z-score model, finding that cash flow when combined with the original Z-score variable is highly significant in predicting the health of UK companies.

Mare, Moreira and Rossi (2017, pp. 348-358) developed advanced techniques for measuring bank insolvency risk. More specifically, they contributed to the existing body of research on the Z-Score introducing novel estimators whose aim is to effectively capture non-stationary returns.

The possibility of forecasting the financial status of a firm is also analyzed in some papers that studied the wider topic of credit risk. Among others, Doumpos, Kosmidou, Baourakis and Zopounidis (2002, pp. 392-412) explored the performance of the M.H.DIS method (Multi-group Hierarchical DIScrimination) to develop a credit risk assessment model using a large sample of firms derived from the loan portfolio of a leading Greek commercial bank.

Allen and Saunders (2003, pp. 1-32) examined how macroeconomic and systematic risk effects are incorporated into measures of credit risk exposure. Allen, DeLong and Saunders (2004, pp. 727-752) studied the most recent Bank of International Settlements proposals for the credit risk measurement of retail credits in capital regulations.

Yu, Wang and Lai (2008, pp. 1434-1444) proposed a multistage neural network ensemble learning model to evaluate the measurement of credit risk while Khashman (2010, pp. 6233-6239) described a credit risk evaluation system that uses supervised neural network models based on the back propagation learning algorithm.

Despite the criticisms mentioned above, Altman's Z-score continues to be very commonly used. Even if some of the studies quoted above have addressed how to resolve the different limits of the Altman model singularly, none of them have attempted to resolve more than one of the limits simultaneously, as this study specifically proposes. For this reason, this study could fill a gap in the existing literature by attempting to verify if the simultaneous consideration of (i) subgroups of non-defaulting and defaulting firms that reflect the actual composition of the population, (ii) different variables with respect to those generally used in the Altman model or in its main variants, and (iii) a panel approach, could lead to a significant reduction of the forecasting error of the financial status of a firm.

3. The Methodology and Model

As stated above, some variations on Altman's approach are suggested with the aim to obtain better results in terms of a firm status (defaulting/non-defaulting) forecast and then an improvement in the *a priori* evaluation of a firm insolvency risk. So,

1) after the original Altman model implementation on a "50-50 group" of firms extracted by the dataset used,
2) the same procedure was applied to a "nd-d group" of firms, where the values of "nd" and "d" reflect the actual non-defaulting/defaulting composition of the population in the considered data set. Then,
3) (via a multi-collinearity analysis) new possible explicative variables of the default status were built, selected, and tested to divide (applying again a discriminant analysis) the considered firms of a "nd-d group" in the two cluster of non-defaulting/defaulting units;
4) finally, a new way (i.e. a panel regression analysis) to divide the dataset firms into the two clusters of non-defaulting/defaulting units on the basis of the previous selected explicative variables was proposed.

As for item 4), one of the most heated contested issues in the scientific debate is the choice of the statistical method to design models for insolvency risk prediction. For this purpose, multiple regression models with a dichotomic dependent variable are very frequently used. Actually, a wide literature (Maddala 1983, 1992) analyses potentialities and limits of such methodologies. Despite their own criticism, discriminant analysis and multiple regressions continue to be of great interest for banking operators that search for new methods for credit approval process.

In many contributions the classification into the subsets non-defaulting/defaulting firms is obtained by employing at the same time linear discriminant analysis and logistic multiple regression (Mossman et al. 1999). Then the researchers choose the model with the best performance out of the sample, testing by this way non sample-specific results derived from an overfitting (and consequently the model inability to provide generalizations).

Actually, also in the empirical analysis, two approaches are compared, i.e. linear discriminant analysis, because of the legacy from the first model put forward by Altman, and panel regression. Summarizing the pros of the last method, panel data are characterized by a greater wealth of information both with respect to time series and to cross-sectional data. If available, panel data are preferable also because the information which is supplied from the temporal dimension is able to contain to a great extent, if not eliminate completely, the problem of heteroscedasticity which occurs in cross-sectional multiple regression (Baltagi 2005). In contrast with the analyses carried out exclusively in a spatial dimension, temporal information (within or intra-individuals) are in fact considered. They allow giving an answer to the question (considering the characteristics of the firm given) of whether institutional events or policy changes can have a certain effect on the relationship being analyzed over time. On the other side, in contrast with analyses which are purely based on time series, panel data also consider information grasped by each individual (between or inter-individuals) which, in the context of analysis, (considering given institutional events or changes in policy over time) allows the question about whether the specific characteristics of the considered firms can have an effect on the relationship being analyzed to be answered.

With a panel data, therefore, assumptions that are more complex can be investigated (concerning dynamics, but also micro and macroeconomic characteristics). The high number of observations (from n or T to n*T) also allows both a better estimate of parameters and a more appropriate use of asymptotic statistical properties. This wealth of information allows the use of more than one estimation strategy, so that the parameters in object can be identified using the variability of data in a time dimension, cross-sectionally or both.

4. The Findings

The considered data covers a period from 1999 to 2015 and refer to Italian manufacturing firms from Marche, the only region in Italy having more than 40% of persons employed in industry as a proportion of those employed in the non-financial business economy (Eurostat 2011).

In particular, this work begins from a closed set of 144 manufacturing firms in 1999 that, because of company crisis, progressively reduced becoming 96 in 2015. They all are limited and unlisted firms selected via a series of stratifications that consider the firm size, the specialization in the sector and the presence in the territory. This set of companies is particularly suitable for this research objective since it provides economic and financial information during seventeen years about a consistent number of firms that are those that actually have the more relevant weight in the local economy.

4.1 Implementing the Original Altman Model on a “50-50 group” of Firms

The analysis begins with the implementation of the original model suggested by Altman in 1968 on the described dataset.

Following his procedure, a group made up of all the defaulting firms (48 units) and the same number of non-defaulting firms was set up (in this way the “50-50 group” of firms was created). For defaulting firms, the balance sheet data of the final year of normal operation was considered. In order to select the non-defaulting firms, for each failed firm a healthy firm in the same sector, in the same year, and of similar size was randomly chosen (considering as a proxy of the latter firstly the total assets and then the turnover).

For parameters estimation, the data set that covered the period 1999-2010 was used in order to have a good representation of the defaulting firms in the test set (2011-2015) used to quantify the forecasting errors. Stating that, in the "50-50 group", the five default probability explanatory indicators values suggested by Altman were calculated, a discriminant analysis was run and, finally, the type I and II errors were quantified.

The type I and II errors resulting from this procedure are respectively 22,2% and 33,3% (data available upon request), therefore not modest as on the contrary emerged in Altman's implementations and moreover worrying especially in terms of the high incidence of failing to pinpoint defaulting firms.

4.2 Implementing the Original Altman's Model on a "nd-d group" of Firms

Whether the choice of a "50-50 group" might be behind the previous disappointing results - as many authors have already reported (Eisenbeis 1997) - was considered.

Really, in a normal economic context, it is difficult to find the same number of companies which are non-defaulting and defaulting, since there are more of the former than the latter. This topic appears also within the considered data set, since a "67-33" distribution between non-defaulting and defaulting firms results. Therefore, all dataset information was used.

Specifically, for the 48 defaulting firms (now corresponding to 33%) once again the data of the last year of normal operations was chosen. In relation to the other 96 non-defaulting units, such as the residual 67%, a single year balance sheet data selected on the defaulting firms temporal distribution was utilized.

As in the previous section, for parameters estimation, the data set that covered the period 1999-2010 was used while for quantifying the type I and II errors that of 2011-2015 was referred to. The type I and II errors resulting from this procedure are respectively 22,2% and 27,8%. Despite this improvement in the overall performance, there was no change, however, in the incidence of type I error.

4.3 Building and Selecting New Explicative Variables for a Discriminant Analysis on a "nd-d group" of Firms

As the previous results were disappointing, the research proceeded by testing the possibility of specifying new explicative variables for the firm crisis.

Based on the available information, 18 balance sheet indicators (listed in Appendix) were calculated (they can be subdivided into financial structure and asset solidity, liquidity, profitability, financial management and extraordinary management ratios).

Building (and then selecting) the explicative variables of a firm default probability, the above "67-33 group" was referred to because of its best theoretical and empirical performance, as described in previous section. All the indexes values were standardized to avoid the problem linked to their different scale. As a result of a multicollinearity analysis (to this aim we used IBM SPSS Statistics 23) 13 indicators were selected.

Then, carrying on a discriminant analysis, only the following five variables were statistically significant and linked to the dependent variable as expected in theory:

1. roi = EBIT / Total assets

2. fe/va = Net financial expense/Value added
3. at = Sales / Total assets
4. e/fa = Equity / Net fixed assets
5. roe = Net income / Equity.

As in the previous section, for parameters estimation the data set that covered the period 1999-2010 was used, while for quantifying the type I and II errors that of 2011-2015 was referred to. Despite the improvement in the overall performance due to a lower value of the type II error (11.1%), an unchanged type I error remained (22.2%). As consequence, it became very important to try to use a different approach to estimate the model parameters.

4.4 A Panel Regression Analysis to Forecast the Status of a Firm

Stating the previous, it was attempted to divide the considered firms into the non-defaulting/defaulting groups via a panel regression analysis.

As it is widely known, the panel fixed effects estimator concentrates on the data variation within every statistical unit and is based entirely on time variation in data. In this analysis, this type of estimator was used for a number of reasons. Firstly because the data available are a closed and complete set of information: the literature shows that in this case fixed effects are the natural candidates as they have the advantage of being able to capture effectively (or to test) all the relevant variables which are idiosyncratic with respect to statistical units which are fixed in time (Baltagi 2005). Secondly, the data showed a good variation in the time dimension (17 years) to be able to justify the use of a within estimator. Thirdly, the least squares with dummy variables (LSDV) estimation method, which is the procedure in the fixed effects context, is BLUE (i.e. the Best Linear Unbiased Estimator) if (i) the model is really of the type $y_{it} = \alpha + bx_{it} + \sum_{j=1}^{N-1} \mu_j D_{ji} + \varepsilon_{it}$ (ii) x is slightly exogenous and if $\varepsilon_{it} \mathrm{IID}(0, \sigma_\varepsilon^2)$ and (iii) it is in any case consistent even though the true model is a random effects model. In any case, during the implementation a Hausman test was run that assessed the fixed effect estimator superiority.

Let $X^{(j)}$ be the *j-simo* regressor in the model while y_{it} represents the firm status associated to each statistical unit $(i = 1, \ldots, n)$ at time t $(t = 1, \ldots, T)$, such as $y_{it} = 0$ if the firm is defaulted and $y_{it} = 1$ if the firm is non-defaulted. Then in the context of analysis, the equation to estimate is the following:

$$y_{it} = \alpha + \sum_{j=1}^{N} b_j x_{it}^{(j)} + \varepsilon_{it} \tag{2}$$

where the error term is equal to a fixed effect plus a true idiosyncratic term $\varepsilon_{it} = \mu_i + w_{it}$.The fixed effect μ_i “absorbs” all the variables which are fixed in time and every other fixed time factor which may be relevant and which has not been considered explicitly.

With the aim to obtain dependent variable values (i.e. the non-defaulting/defaulting status) inside the zero-one interval, logit model was implemented. Due to the progressive exit of defaulting firms, the panel data used to develop this part of analysis was obviously non-balanced. To fill the information gaps, which gradually began to appear in relation to these firms, the values relating to the last available year before failure were repeated, as is usual practice (Stock & Watson 2014).

The same five indicators used in the last discriminant analysis begin being considered as explicative variables. Now, the training set covers the period between 1999 and 2014, while the 2015 data is used as test set. In Table 1 are the parameters' values of the best-estimated model.

Table 1. Logit panel regression: results obtained from a fixed-effects estimator (dependent variable: firm status)

Regressors	Coefficients	Std. Err.
roi	1.359705*	0.2179739
at	2.006727*	0.3538376
e/fa	1.438880*	0.3732217

As can be easily seen, only three out of five of the previous firm status explicative variables were statistically significant. In relation to the forecasting error, type I error is now lower than in the previous case (16.7%) while, on the other hand, type II error substantially increases (from 11.1% to 52%). Therefore, this particular specification of the model is probably too precautionary.

To improve the obtained results a way could be to select different variables among the starting 18. To this aim, after conducting another multicollinearity analysis on the panel data that cover the period 1999-2014, a new logit fixed effect panel regression was carried out. In Table 2 are the parameters' values of the best-estimated model.

Table 2. Logit panel regression: results obtained from a fixed-effects estimator (dependent variable: firm status)

Regressors	Coefficients	Std. Err.
cf/a	1.6761390*	0.2443542
re/a	1.3338600*	0.3903897
at	2.6229120*	0.3995040
em/a	-0.4988454*	0.1859305

where
1. cf/a = (Net income + Depreciation + Amortization) / Total assets
2. re/a = Retained earnings / Total assets
3. at = Sales / Total assets
4. em/a = Extraordinary management results / Total assets

In relation to the forecasting error, type I and II errors (respectively 12.5% and 20.9%) are now lower than the previous case.

4.5 Discussion

From an organizational point of view, the good health of a firm is the result of the coexistence of financial, economic and organizational balances. This determines a company's ability to thrive in the market. At the organizational level, the mentioned balance is generally explained by measuring the degree of efficiency and effectiveness of a firm.

In the managerial field, the concept of efficiency is usually accompanied by that of effectiveness. Effectiveness mainly concerns the relationship between the achieved results

and the objectives set, while the concept of efficiency refers to the relationship between the achieved results and the resources used. In other words, efficiency is generally measured as ratio between output and inputs. This is directly related to the firm's ability to use combinations of productive factors (corporate assets) in the best possible way to achieve the set objectives (effectiveness), maximizing the company's economic performance (efficiency) (Baum & Wally 2003).

Among the 18 indicators used in this study, the last four selected by the statistical analysis express with determination the concepts of organizational effectiveness and efficiency. Moreover, each of them presents in the denominator the total assets of the firm that represents and summarizes an economic measure of the organization of the same. In summary, it is therefore possible to state that each of the four indicators finally selected represents a measure of the firm's efficiency in combining production factors (resources, inputs) to achieve the expected result (output).

In more detail, from an analysis of each part of the indexes, it can be stated that:

- the first, represented by cf/a, shows that the firm's cash flow is a measure of its capacity to achieve a resulting economic net of the effects of financial amendment of the depreciation of receivables and inventories (dependent on external conditions of the firm) as well as the accounting effects of amortization and depreciation. The ratio of cash flow to total assets can be interpreted as a measure of a firm’s efficiency to combine production factors in order to achieve a positive result of firm management;
- the second, represented by Re/a, shows that the retaining earnings represent the share of net income that the firm wants to use in order to improve its organization, or increase the level of its investments using its ability to produce income. This ability can be defined as an index of the possibility of a firm to improve its operational effectiveness (new products, new markets, new customers), as well as its production efficiency (new plants to increase production capacity or to reduce the cost of the production itself). The ratio with respect to total assets makes it possible to define the level of efficiency of the firm's development with respect to its current organizational configuration;
- the third, represented by At, shows that the level of sales highlights on the one hand, and the effectiveness of the firm to conquer and maintain market shares on the other, compared to total assets, represents a measure of the efficiency of the sales process. This measure determines the firm's ability to use the current organizational configuration to place its products on the market. It is obvious that in an expanding or shrinking market, a change in sales with the same business configuration (total assets) is a predictor of a firm's capability to produce more or less income in the future;
- the fourth, Em/a, reveals, from an organizational point of view, that the result of the extraordinary management inversely represents a measure of the firm's effectiveness (i.e. producing results through the activities of its core business), and its relationship with the total assets represents the inverse measure of its efficiency in combining the productive factors to obtain an economic result from these activities.

For what has been said, it is reasonable to state that all the indexes described above are able to fully grasp many important aspects of the actual financial status of a firm and therefore, as a direct consequence, can be very useful in a predictive analysis like the one proposed in this paper.

Moreover, the specific characteristics and novelty aspects of the proposed approach - such as the simultaneous consideration of (i) subgroups of non-defaulting and defaulting firms that reflect the actual composition of the population, (ii) different variables with respect to those generally used in the Altman model or in its main variants, and (iii) a panel approach seem, when joined together, to lead to a significant reduction of the forecasting error of the financial status of a firm.

This result is quite interesting: the model seems to be able to attentively forecast a firm's bankruptcy while simultaneously being prudent towards those firms that present signs of difficulty.

5. Summary and Conclusions

The use of the fixed effects panel regression on medium-large sized Italian firms set allows a good assessment of the status of a firm in terms of type I and II errors, with suitable statistically significant coefficients. Moreover, this approach provides a better assessment of the firm status than the Altman-style discriminant analysis or its variants.

From the data set, it emerges that:

- a more realistic firms distribution in the non-defaulting/defaulting subgroups (67%-33%) can reduce the error size;
- the firm status explanatory variables are the standardized values of the cash to assets ratio (cf/a), the retaining earnings to assets ratio (re/a), the assets turnover ratio (at), and the extraordinary management to assets ratio (em/a);
- the forecasting error of a logit fixed effect regression model is 16.7% overall (12.5% type I error and 20.9% type II error). Type I error, the most worrying, is noticeably lower than the analogous obtained by the Altman original model and by its described variants.

In addition to the good statistical evidence that the proposed approach shows in relation to its ability to forecast the default of the analysed firms, it can also be said that the indexes used within it are actually representative of the organizational aspects of a firm. This means that, compared to other similar ratios, the indexes used in the proposed procedure focuses on balance sheet relationships strongly correlated with the concepts of organizational effectiveness and efficiency. If dysfunctions or inefficiencies become evident in the management of a firm and therefore negatively affect the result of management, the presence of an organizational imbalance will inevitably affect the firm’s economic and financial profile that, as a consequence, will be negatively affected.

In the proposed approach to forecast the financial status of a firm, the indexes used takes into consideration values and aspects that concern the organizational capacity of the firm and not exclusively financial and equity measures of the same. For this reason, they are certainly able to provide information on many aspects intimately linked to the current state of a firm and so seem particularly suitable for the forecasting purposes.

None of the previous research on this topic has found these results because this study is the first to simultaneously consider subgroups of non-defaulting and defaulting firms that reflect the actual composition of the population, different variables with respect to those generally used in the Altman model or in its main variants, and a panel approach. This work has been able to clearly verify that a particular attention simultaneously directed at all of these aspects is able to lead to a significant reduction of the forecasting error of the financial status of a firm.

This result is quite interesting because the proposed approach seems to be able to attentively forecast a firm's bankruptcy while being simultaneously prudent towards those firms that present signs of difficulty.

As future development of this research, a larger data set would be used in order to consider a more exhaustive economic area and to test the forecasting ability of the model in relation to different economic sectors. Variables would also be inserted to allow the evaluation of the intangible assets of a firm and its eventual capacity to obtain financing from third parties, and the economic trends in our approach.

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Appendix

List of the considered balance indexes.

e/d	equity to debt ratio	$\frac{\text{Equity}}{\text{Total liabilities}}$
nd/a	net debt to assets ratio	$\frac{\text{Net debt}}{\text{Total assets}}$
nd/s	net debt to sales ratio	$\frac{\text{Net debt}}{\text{Sales}}$
cl/ebitda	current liabilities to ebitda ratio	$\frac{\text{Current liabilities}}{\text{EBITDA}}$
re/a	retaining earnings to assets ratio	$\frac{\text{Retaining earnings}}{\text{Total assets}}$
cf/a	cash flow to asset ratio	$\frac{\text{Net income} + \text{Depreciation} + \text{Amortization}}{\text{Total assets}}$
c/a	cash to assets ratio	$\frac{\text{Cash}}{\text{Total assets}}$
cr	current ratio	$\frac{\text{Current asset}}{\text{Current liabilities}}$
wc/a	working capital to asset ratio	$\frac{\text{Current asset} - \text{Current liabilities}}{\text{Total assets}}$
i/s	inventory to sales ratio	$\frac{\text{Inventory}}{\text{Sales}} * 360$
dso	days sales outstanding	$\frac{\text{Receivables}}{\text{Sales}} * 360$
e/fa	equity to fixed assets ratio	$\frac{\text{Equity}}{\text{Net assets}}$
vap	value added productivity per employee	$\frac{\text{Value added}}{\text{Number of employees}}$
at	assets turnover ratio	$\frac{\text{Sales}}{\text{Total assets}}$
roi	return on investment	$\frac{\text{EBIT}}{\text{Total assets}}$
roe	return on equity	$\frac{\text{Net income}}{\text{Equity}}$
fe/va	net financial expense to value added ratio	$\frac{\text{Net financial expense}}{\text{Value added}}$
em/a	Extraordinary management to assets ratio	$\frac{\text{Extraordinary management}}{\text{Total assets}}$