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PROBLEMS IN PREDICTING TARGET FIRMS AT THE UNDEVELOPED CAPITAL MARKETS

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Abstract. *Taking into account the characteristics of the undeveloped capital markets, it is often very difficult to create appropriate prediction models for corporate M&A. This study focuses on the recent developments of discriminant analysis, logistic regression analysis and artificial neural networks (ANN) with regards to the identification of potential takeover targets. The authors analyse explanatory and predictive capabilities of the ANN and disscuss various limitations and problems attached to ANN application in M&A modelling at the undeveloped capital markets.*

Key Words: *Target firm, acquisition, artificial neural networks, undeveloped capital markets*

INTRODUCTION

During the last decade, a significant growth of the global merger and acquisition (M&A) activity, has been observed. Corporations realize M&A as external growth strategies for various reasons such as sinergy, taxation, diversification, improved management, survival, etc.The field of M&A is undergoing rapid change. It has reached new hights in the first decade of the XXI century that eclipse the peaks set in the 1980s. The level of global M&A activity has exceeded $1.9 trillion in 2004. This is an increase of 40% of the worldwide M&A volume in 2003.[1]

While there are company specific motives for undertaking these external growth strategies, there are also massive economic factors which have caused such a high level of global M&A activity. M&A transactions have been intensified as the response of globalization, liberalization, increase in competition, regional economic integrations creation, etc. Economic reforms, including privatization of state enterprises undertaken by many developed and undeveloped countries, have emphasized competition and free markets giving a positive attitude to acquisitions as types of foreign direct investments. All those

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[1] Source: Thompson Financial Securities Data

factors result in an increasing number of potential target firms in the global economy and esspecillay at the undeveloped capital markets.

The potential target firm identification, therefore, becomes the area of great research interest, both to business and academia. Much of the literature has been devoted to forecasting M&A. Some of the techniques applied in forecasting M&A activity involve the use of either discriminant analysis or logistic regression. They summarise information contained in a firm's financial statements by using statistical aggregation to assess a firm's financial status. A possible improvement could arise via the use of Artificial Neural Networks (ANN), which, since their first applications to financial analysis, have produced some promising results.

Taking into account the characteristics of the undeveloped capital markets, it is often very difficult to predict and choose suitable target firms, i.e. to create appropriate prediction models for corporate M&A. Having rewieved empirical evidence on the characteristics of target firms in the first section, we discuss recent developments of neural networks with regards to the identification of potential takeover targets. In section 2, ANN are compared with the traditional statistical techniques of discriminant analysis and logistic regression. Numerous problems associated to ANN application in target prediction at the undeveloped capital markets and predictive capabilities of ANN are analysed in section 3. The conclusions of the study are presented in section 4.

1. ACQUISITION ACTIVITY AND INDETIFICATION OF POTENTIAL TARGET FIRMS

Acquisitions and mergers as forms of the market of corporate control activity are the theme of constant discussions and contrasts among professionals and society in general. Millions of dollars included in those transactions do not mean only money flow, but they open numerous questions and cause multiplicative movements on capital, money and labor markets, as well as product markets of the enterprises included in those transactions. Viewed through historic prism of development of theories of M&A, it is to be seen that corporate control market through M&A provides mechanism by which business units, that operated independently, become objects of coordinated management and control. To say it more concretely, as H. Manne [10] states, the market for corporate control is the best way of making inefficient management disciplined.

M&A are interesting and complex financial, investment and management business ventures. For the illustration of complexity and sequence of activities in the process of M&A realization, the conceptual frame that includes the following phases may be used:

- recognizing needs and implication of external growth on enterprise development strategy,
- setting objectives and limitations on the basis of which the candidate for M&A is to be studied,
- identification and valuation of the target company, where financial and market position of the target enterprise are to be settled on the basis of deep analyses, valued its production program and possible implications on synergy,
- preparation of the negotiations platform, and
- making decision on M&A and preparing a plan of post-acquisition smooth-operation.

The third phase, ie. the area of identification and prediction of potential target companies has been of an increasing scientific interest during the last decades. Analysing the stock market selection process involves looking at the pre-merger financial characteristics of various groups of firms defined by their involvement in M&A activity (and, in addition, examining their post-merger performance). Over the last decades, much research has concentrated on analysing M&A activitiy examining a wide array of economic advantages that are believed to give rise to mergers. But most of the models focus more on economic motivation, do not take into account simple basic statistical issues.

Previous studies have not produced a generally agreed list of factors leading to M&A. Singh analyses the economic and financial characteristics of acquired firms and compared them with those of firms not taken over. The main objective of his study is to investigate methods to discriminate between taken-over and surviving firms, acquiring and acquired firms, acquiring and non-acquiring firms. Ten basic variables measuring accounting ratios, and information on share prices and stock market valuation of the firms are used for the estimation of different univariate and multivariate discriminant models. Simkowitz and Monroe [15] suggest that target firms tend to be relatively small, have relavively lower P/E and dividend payout ratio and lower equity growth. They further observe that non-financial characteristics appeared to be important. Their multivariate discriminant analysis in-sample results correctly predict 83% of the targets and 72% of the non-targets, while the holdout results are slightly worse predicting 64% of the targets and 61% of the non-target.

Stevens [16] finds that target firms are more liquide and tend to have lower financial leverage. Huges [7] summarizes the results of several empirical research on target firms' pre-merger characteristics. These results suggest that, whilst there are some important variations across time periods and a type of M&A, targets have worse short-term profitability growth records, are smaller, less dynamic and somewhat less highly valued that companies on average.

The paper by Palepu [12] emphasises that lower excess return, lower leverage, and smaller size are likely to increase a firm's probability to be acquired, while a liquidity variable, market-to-book ratio and price-earning ratio are statistically insignificant. The predictive ability of the model is tested on a holdout sample made of 30 takeover targets and 1087 non-targets. The magnitudes of the estimated acquisition probabilities are in general very small (45%).

Chen, Weinberg, Randy, Yook [3] apply a standard feedforward backpropagation neural network with a single hidden layer to identify potential takeover targets and the possibility to yield positive abnormal returns from investing in these targets stocks. The variables applied to the neural network models account for size, leverage, liquidity, growth rate, dividend payout, price-earning ratio, return on equity, Tobin q ratio and industry. An important feature of this study is the adoption of a cost function to account for the different predictive accuracy of the two categories (acquired and unacquired). Overall the results are quite promising. The out-of-sample overall prediction rate is over 70% and the cumulative and daily average return of the portfolios identified by the neural network is significantly higher than the market average return.

Harford [6] finds that firms charaterised by lower liquidity, higher market-to-book ratio, and cash-rich firms are less likely to be targeted. In addition to these studies, North [11] finds that target firms can be characterized as having lower managerial ownership and higher ownership by outsiders.

Table 1.1. Previous studies on the characteristics of target firms*

Researcher	Country	Method	Classification (%)	Prediction (%)
Simkovitz and Monroe (1971)	USA	MDA	77	63.2
Tzoannos and Samuels (1972)	UK	GLS	70	–
Stevens (1973)	USA	MDA	70	67
Belkaoui (1978)	Canada	DA	72	70
Wansley and Lane (1983)	USA	MDA	77.3	69.2
Dietrich and Sorensen (1984)	USA	Logit	92.5	–
Rege (1984)	Canada	MDA	–	–
Bartley and Boardman (1996)	USA	MDA	65	–
Palepu (1986)	USA	Logit	–	46
Bartley and Boardman (1990)	USA	MDA	82.5	–
Ambrose (1990)	USA	Logit	65.1	75.6
Barnes (1990)	UK	MDA	68.5	–
Ambrose and Megginson (1992)	USA	Logit	74.3	–
Walter (1994)	USA	Logit	65	66

*DA, discriminant analysis; GLS, generalized least squeres;
MDA, multiple discriminant analysis; -, not reported.

Source: Barnes, Paul (1998), Can takeover targets be identified by statistical techniques?: some UK evidence, The Statistician, 47, Part4, pp.573-591

In Barnes's study [1] the prediction results of the above cited studies are compared according to prediction method and prediction success (Table 1.1). As can be seen, logit and discriminant analysis are predominant reseach methods used in these studies. In the next section, these traditional statistical techniques are compared to artificial neural networks, as a technique with possibly better explanatory and predictive capabilities in the field of mergers and acquisition activity.

2. METODOLOGY DESCRIPTION

Discriminant analysis and logistic regression summarise information contained in a firm's financial statements by using statistical aggregation to assess a firm's financial status. Artificial Neural Networks (ANN) present a possible improvement in statistical instrumentarium used for potential target identification.

2.1. Discriminant analysis

Discriminant analysis (DA) is a statistical technique which allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously. Depending on whether the behaviour of variables is jointly determined or considered individually, DA models can be further subdivided into two categories:

- univariate models;
- multivariate models.

The multivariate technique has the advantage of considering an entire profile of characteristics common to the entities, as well as their interaction, while the univariate approach limits its analysis to only one characteristic at a time.

DA derives the linear combinations from an equation that takes the following form:

$$Z = W_1X_1 + W_2X_2 + ... + W_nX_n$$

where

Z = discriminant score

W_i (i = 1, 2, ... , n) = discriminant weights

X_i (i = 1, 2, ... , n) = independent variables, the financial ratios

DA does very well provide that the variables in every group follow a multivariate normal distribution and the covariance matrices for every group are equal.

2.2. Logit analysis

Logistic regression analysis has been used to investigate the relationship between binary or ordinal response probability and explanatory variables. Binary logistic regression, a nonlinear model, is one of the predictions techniques with few assumptions and the dependent variable is a binary or dummy variable. Very few assumptions are required in this model in comparison to other similar dependence techniques such as discriminant analysis. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices as DA does. In logistic model, the probability of occurring of an event is estimated directly.

The probability of an event occuring = $e^Z/(1+e^{-Z})$

where Z is the linear combination $Z = B_0 + B_1X_1 + B_2X_2 + ... + B_nX_n$, and n is the number of independent variables.

The probability of the event not occurring is estimated as

$$\text{Prob (no event)} = 1 - \text{Prob(event)}$$

The method fits linear logistic regression model for binary or ordinal response data by the method of maximum likelihood. The response variable in the logistic model was a binary variable with the value 1 for target companies and 0 for non-target companies. In logistic regression, the parameters of the model are estimated using the maximum likelihood method where the coefficients that make our observed results most likely are selected.

2.3. Artificial neural networks (ANN)

ANN consists of a large number of processing elements, *neurons*, and connections between them. It implements a function f that maps a set of given input values x to some output values y: $y = f(x)$. ANN tries to find the best possible approximation of the function f. This approximation is coded in the neurons of the network using *weights* that are associated with each neuron. The weights of an ANN are learned using an iterative procedure during which examples of correct input-output associations are shown to the network and the weights get modified so that the network starts to mimic this desirable input-output behaviour. Learning in a neural network then means finding an appropriate set of weights.

ANN is an emerging flexible tool in the area of data modeling, particularly useful if knowledge about the inherent complex relationship among the data elements is not available or not assumed. It uncovers cause and effect relationships and identifies different patterns, which are difficult to detect by other tools. A general heuristic for the design of neural networks in financial domains is that the more knowledge that is available to the neural networ for forming its model, the better the ultimate performance of the neural network, with a minimum of two years of training data (more then 500 records) a nominal starting point.

Development of high-quality network models is difficult [8]. Most neural network designers develop multiple ANN solutions with regard to the network's architecure. However, two critical design issues still face financial modelers desiring to use ANN: selection of appropriate variables and capturing a sufficient quantity of training examples to permit the neural network to adequately model the financial time series [8].

ANN have many advantages over conventional methods of analysis. First, they have the ability to analyze complex patterns quickly and with a high degree of accuracy. Second, ANN make no assumptions about the nature of the distribution of the data. They are not, therefore, biased in their analysis. Third, since time-series data are dynamic in nature, it is necessary to have non-linear tools in order to discern relationships among time-series. ANNs are best at discovering these types of relationships. Fourth, neural networks perform well with missing or incomplete data. Fifth, compared with an econometric model, it is easier to use ANNs where a forecast needs to be obtained in a shorter period of time.

Yoon and Swales [20] compare ANNs to DA. The technique of DA is generally used to build a procedure that not only considers the number of correct and incorrect classifications of the data but also takes into account the cost of each type of classification. Yoon and Swales show that the prediction of stock price performance based on an ANN model is superior to prediction based on a discriminant analysis.

Surkan and Singleton [17] find that ANN models perform better than DA also in predicting future assignments of ratings to bonds. This may lead to an inaccurate assumption of determinacy, where - given a set of initial conditions - it may be presupposed that future prices of stocks and bonds may be predicted. However, the actual values (or ANN outcomes) fluctuate unpredictably, indicating a noticeable behavior of indeterminacy. Trippi and DeSieno [18] apply an ANN system to the modeling of trades in Standard and Poor's 500 index futures. They find that the dynamics of the ANN system helps to outperform a passive approach to investment (a buy-and-hold strategy) in the index; thus, they favor the implementation of ANNs to the financial decision making process.

However, there are some drawbacks connected with the use of ANN. For one, ANN are not all-purpose problem solvers. Thus far, there is no structured methodology available for choosing, developing, training, and verifying an ANN. There is no standardized paradigm for development. The output quality of ANNs may be unpredictable regardless of the design and implementation schedule. Some researchers maintain that no estimation or prediction errors are calculable when using ANN [2] due to constant "learning" by the process. Also, ANNs are "black boxes" - it is impossible to figure out how relations in their hidden layers are estimated [4, 9]. Another drawback is that ANNs have long training times. Reducing training time is crucial because building a neural network forecasting system is a process of trial and error; hence, the more experiments a researcher can run in a finite period of time, the more confident he can be of the result. The network also tends to base its predictions of future events on "memories" of similar situations from the past [14].

ANNs tend to under- or over- fit data [4]. It is always possible to build a neural net or a mathematical function that exactly fits all the historical data such as a time series, but the predictive capability of such a system is relatively nonexistent. This over-fitting is because the noise and anomalies in the data do not allow the net to predict with any accuracy.

In the case of financial markets, neural nets quantify the influence of major financial variables and the impact that these relationships have on the future price movement of the target market [5]. Recent research also suggests that neural networks may prove useful to forecast volatile financial variables that are difficult to forecast with conventional statistical methods, such as exchange rates and stock performance [13].

3. EXPERIMENTAL VARIABLES AND PROBLEMS IN MAKING DATA SET AT UNDEVELOPED CAPITAL MARKETS

Possible explanations for the inconsistent results of the above cited studies on M&A target prediction include the changing of corporate control environment, constantly evolving M&A motives, different model specifications and time horizonts used in the studies by different researchers. To some extent the above studies suggest that the market has a problem with appropriately valuing companies at the margin. The problem becomes even bigger at the undeveloped capital markets. Nevertheless, it can be generally said, that financial variables can, and have been used, to model M&A activity. Relying on accepted theories on M&A, we select those financial variables that, in our opinion, have the biggest impact on acquisition activity at the undeveloped capital markets. Table 3.1 presents our selection of 14 variables which have been drawn from the M&A literature. It also gives comments on the capability of each variable to be satisfactorily used as an ANN input for the purpose of target firms' identification and prediction.

Table 3.1. List of financial variables used as ANN inputs

Variable	Description	Comment
Size	Log of total net book value	Unreliable data set
Valuation	Net profit / Market value	No information on market value for the most companies
Valuation	Market value/Net tangible asset	No information on market value for the most companies
Leverage	Long term debt / Total asset	Inflation impact is dominant
Profitability	Operating profit / Total sales	Unreliable data set
Liquidity	Current assets / Current liabilities	Limited data basis
Liquidity	Cash and equivalent/Total assets	Limited data basis
Sales growth rate	(Net sales_1-Net sales_0)/Net sales_0	Unreliable data set
EPS growth rate	(EPS_1-EPS_0)/EPS_0	Limited data basis due to small number of public companies
Price-earnings ratio	Stock price / Earnings per share	Limited data basis due to small number of public companies
Dividend policy	Dividend per share / Earnings per share	Limited data basis due to small number of public companies
Activity	Total sales / Assets employed	Unreliable data set
Tobin Q ratio	(Market value of equity+ preffered stocks+debt)/Total asset	No information on market value for the most companies
Interest cover	Operating profit/Total interest	Unreliable data set

The restriction of limited data at the undeveloped capital markets makes the target model selection and prediction-risk estimation more difficult. Those markets are faced with an acurate data deficiency with respect to financial and business operations related to M&A. National Securities Commisions possess only limited data bases that may be be both unreliable and insufficient for the construction of appropriate time series. A limited training set results in a more severe bias-variance (or underfitting versus overfitting) trade-off, so the model selection problem is both more challenging and more crucial. In particular, it is easier to overfit a small training set, so care must be taken not to select a model that is too large. Also limited data sets make prediction-risk estimation more difficult if there is no enough data available to hold out a sufficiently large independent test sample. In such a situation one must use alternative approaches which enable the estimation of prediction risk from the training data, such as data re-sampling and algebraic estimation techniques.

In order to identify potential takeover targets, in which case the sample will consist of firms which were taken over and a further matched set of firms which were not, we can model M&A activity using DA, logistic regression analysis and ANN. The reason behind the choice of ANN is related to the difficulties in the interpretation of the results obtained by ANN. While ANN represents a very powerful instrument in terms of forecasting, its lack of testing devices for the significance of the variables could restrict its applicability to some areas of economic and finance. Moreover, while it is very intuitive to interpret the coefficient achieved by a logit or a DA model, there are no robust methods for interpreting the optimal weights achieved by a NN model, especially if the network architecture contains more than one hidden layer. Therefore, the optimal combination of these three methodologies may shed light on this under-researched area, improving both our understanding of the economic and financial reasons behind this phenomenon and the accuracy of prediction for this problem.

CONCLUSIONS

Recently, a growing interest in neural networks as a tool for data analysis has been observed. To a certain extent, the popularity of ANN compared to other statistical methods may have been caused by the factors mentioned previously, but other issues cannot be ignored. First of all, there is a failure of statisticians to communicate their methodologies and algorithms to non-statisticians. In fact, the vast amount of accumulated statistical knowledge erects a barrier for potential consumers of their methods. ANNs, on the other hand, are in an embryonic phase, which means that the accumulated knowledge is relatively small.

A traditional statistical technique as well as an ANN have been used to model M&A activity at the developed capital markets and to predict potential targets. Cheh, Weinberg & York [3] show that the prediction rate of the ANN is over 70% and that investments in acquisition of predicted targets yield to significant positive abnormal returns. In the case of undeveloped capital markets, the ANN's classificatory performance could be superior compared to the other classical statistical techniques. But, the difference of predictions could also be marginal.

ANN is, however, not free from limitations. One of the limitations is its inability to explain the relative importance of its inputs. It requires sufficiently large number of data sets to train, verify and test the network. On the other hand, at one undeveloped capital (such as in Serbia and Montenegro), the availability of data related to mergers and acquisitions is a problem. Limited data bases, that are in the possesion of National Securities Commisions, could be both unreliable and insufficient for the construction of appropriate time series. Since M&A are growing phenomena at the undeveloped capital market, the potential target firm identification is going to become the area of great research interest. Taking this fact into account, the prediction models' limitations are probably going to be smaller in the near future.

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PROBLEMI U POSTUPKU PREDVIDJANJA POTENCIJALNIH PREDUZEĆA-KANDIDATA ZA PREUZIMANJE NA NERAZVIJENIM TRŽIŠTIMA KAPITALA

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Imajući u vidu karakteristike nerazvijenih tržišta kapitala, kreiranje modela za predvidjanje akvizicione aktivnosti suočeno je sa mnogobrojnim problemima. U radu je analizirana primena diskriminacione analize, regresione analize i veštačkih neuronski mreža (ANN) u identifikaciji potencijalnih takeover targeta. Autori analiziraju eksplanatorne i prediktivne sposobnosti veštačkih neuronskih mreža i ukazuju na ograničenja i probleme povezane sa primenom ANN u modeliranju akvizicione aktivnosti na nerazvijenim tržištima kapitala.

Ključne reči: *Ciljno preduzeće (target), akvizicija, veštačke neuronske mreže, nerazvijena tržišta kapitala.*