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RESEARCH ARTICLE

A comparison of artificial neural network and multinomial logit models in predicting mergers – Draft as of May 2012

Nilgun Fescioglu-Unver[a] and Başak Tanyeri[b]*

[a] *TOBB University of Economics and Technology, Department of Industrial Engineering, Ankara, TURKEY*;

[b] *Bilkent University, Department of Business Administration, Ankara, TURKEY*

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A merger proposal discloses a bidder firm's desire to purchase the control rights in a target firm. Predicting who will propose (bidder candidacy) and who will recieve (target candidacy) merger bids is important to investigate why firms merge and to measure the price impact of mergers. This study investigates the performance of artificial neural networks and multinomial logit models in predicting bidder and target candidacy. We use a comprehensive dataset that covers the years 1979 to 2004 and includes all deals with publicly listed bidders and targets. We find that both models perform similarly while predicting target and non-merger firms. The multinomial logit model performs slightly better in predicting bidder firms.

Keywords: mergers; artificial neural network models; multinomial logistic models

I. Introduction

Merger announcements disclose the intent of bidder firms to purchase control rights in a target firm. Models of target and bidder candidacy are important for three reasons. First, these models allow us to test theories of merger motives. Second,if merger candidacy is predictable, bidder and target shares would reflect the impact of mergers prior to merger announcements. As a result, event study methods that calculate returns around merger announcements may incorrectly measure the price impact of mergers [9, 20, 47]. Event study methods assume that merger announcements are random and measure price impact of mergers in a tight window of time (usually three days) around the announcement. However, mergers are not random. Managers choose to merge. Hence, modeling target and bidder candidacy is important. Third, hedge funds use investment strategies called 'merger arbitrage' that rely on the prediction of bidder and target companies. Merger arbitrageurs realize profits conditional on whether deals are successfully completed [35, 36]. To understand the possible impact of merger arbitrage strategies, one needs to model and estimate merger choice and deal completion. This study investigates the performance of artificial neural network and multinomial logistic models in predicting

*Corresponding author. Email: basak@bilkent.edu.tr; tel:(90-312) 290 1871; fax:(90-312) 266 4958. Both authors contibuted equally and are listed in alphabetical order.

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bidder and target candidacy.

Previous merger studies use two approaches to model bidder candidacy. First approach identifies a single firm characteristic that is used for classification of anticipated and unanticipated bidder firms [5, 16, 23, 32, 34, 42, 44]. Second approach develops predictive models of bidder candidacy that use multiple firm characteristics to classify anticipated versus unanticipated bidders [2, 3, 9, 10, 12, 13, 39, 41]. The contribution of this paper is three-fold. First, this study constructs a comprehensive dataset of publicly listed bidders and targets. The sample covers the years from 1979 to 2004 with 5,207 bidder observations, 2,641 target observations, and 308,079 non-merger firm observations. Second, we estimate bidder as well as target candidacy (instead of estimating only bidder or only target candidacy). Third, the paper runs a horse-race between two methods[1], namely multinomial logit and artificial neural network models.

We find that artificial neural network and multinomial logistic models perform similarly while predicting target and non-merger firms. The multinomial logistic model performs better in predicting bidder firms. Multinomial logistic models yield coefficient estimates that have economic meaning. Artificial neural network models work as a blackbox and do not automatically reveal coefficient estimates. This is why we conclude that multinomial logit models outperform artificial neural network models both in predictive and interpretative performance.

This paper is organized as follows: Section II describes the proxies for merger motives used to model the merger choice, and introduces the multinomial logistic and artificial neural network models used to estimate merger candidacy. Section III compares the results obtained with multinomial logistic and artificial neural network models. Section IV concludes the paper.

II. Research Method

This section develops models to predict the merger choice of firms. At any point of time, managers choose between three alternatives: (i) to propose a bid to attain control rights in another company (bidder firm), (ii) to solicit/receive bids for control rights in their company (target firm), (iii) to neither propose nor solicit bids (non-merger firm). Finance theory proposes several variables that may predict bidder and target candidacy. Following section explains these variables. The next section describes how we estimate bidder and target candidacy using artificial neural network models and multinomial logit models.

Sampling Frame and Description of Variables

We follow the strategy of Cornett et al. [9] and Tanyeri [46] to construct the sample of merging and non-merging firms and to develop predictors of merger candidacy. The sample of merging firms are from Security Data Company's US Mergers and Acquisitions database and cover the period from 11/16/1977 to 12/30/2004. We restrict the merging sample to include those deals in which bidders must hold less than fifty percent of outstanding target shares before the merger announcement and must propose to hold more than fifty percent of target shares after the merger. Sample firms are nonfinancial US enterprises due to the differences in regulatory

[1]Other papers that compare neural network and logistic models include:Adams and Wert [1] who predicts hospital stays, and Cooper [8] who predicts the rescheduling of international debt-service obligations of countries. Hossaina and Nasser [28] compares neural networks and ARMA-GARCH models in forecasting financial returns

environment and the lack of data availability for foreign and financial firms. We also require sample firms to be public companies.

Identical filters are used to construct the nonmerging-firms sample as the filters used in compiling the sample of merging firms. We compile a sample of US, nonfinancial firms using the CRSP-COMPUSTAT merged database. The sample includes 110 quarters starting from the third quarter of 1977 and ending in the fourth quarter of 2004. We map the merging sample onto the CRSP-COMPUSTAT data for identification of bidders, targets and non-merger firms. A firm-quarter is defined as: a bidder-quarter if the firm makes at least one merger bid by the next quarter, a target-quarter if the firm gets at least one bid in the next quarter, and a non-merging firm-quarter if the firm neither makes nor gets any bids in the next quarter. We also require that the firms have non-missing data for variable construction and drop the variables at the 1st and 99th percentiles to reduce the effect of outliers. These filters produce 2,530 firms proposing 5,400 bids in 5,207 firm quarters, 2,352 firms receiving 2,706 bids in 2,641 firm quarters, and 11,010 firms neither proposing nor receiving bids in 308,079 firm quarters.

Table 1 summarizes the sample. First rows list the average book values of assets (in million dollars) of bidder, target, and non-merger firms in each year. Second rows list the number of bidder, target, and non-merger firms in each year. The second half of the sample (covering the years 1991 to 2004) is richer than the first half (covering the years 1979 to 1990) in terms of merging firms. There are, on average 262 bidders and 125 targets per year in the second half and 128 bidders and 74 targets per year in the first half. Bidders prove largest (on average 3,538 million dollars) in terms of book value of assets. Non-merging firms (on average 962 million dollars) are larger than targets (on average 1,421 million dollars). The size distribution indicates that the larger sample firms buy the smaller firms.

We review theories on merger motives to develop predictors for merger candidacy. Managers may engage in mergers to create value for shareholders and/or to protect themselves from losing the non-monetary benefits associated with their managerial positions. Managers may create shareholder value by: (i) increasing efficiency of human and financial capital; (ii) attaining economies of scale and scope; and (iii) increasing market power [15, 17, 21, 27]. Incentive conflicts between managers and shareholders may also lead to mergers when opportunistic managers focus on generating value for themselves at the expense of shareholders [11, 19, 24–26, 40, 43].

Eight variables[1], namely *sales shock, square of sales shock, asset size, asset growth, sales growth, concentration ratio, resource-growth mismatch, and return on assets (ROA)*, represent merger motives to generate shareholder value. *Sales shock* (the absolute value of the two-year median industry[2] sales growth rate minus the two-year median sales growth rate for all sample firms listed in our sample) is a measure of economic disturbances which may motivate mergers [4, 17, 33]. The *square of sales shock* allows for non-linearity in the sales shock variable. The *asset size* (the log of total assets), *asset growth* (the two-year growth rate of assets), and *sales growth* (the two-year growth rate in sales) variables affect the willingness to increase the economies of scale and scope through mergers and therefore reduce costs [3, 17, 37, 39]. The *concentration ratio* variable (tcumulates the sales of the largest four firms -in terms of sales- and divides by total industry sales) measure the ease of entry and exit into the industry [13, 17]. The *resource-growth mismatch*

[1]Interested readers may refer to Cornett et al. [9] and Tanyeri [46] for the definitions and in-depth discussions about the variables used in this study

[2]Its two digit SIC code identifies the industry of a firm. The one-digit SIC code is used when less than five firms exist in an industry.

Table 1. Asset size and distribution of bidders, targets, and non-merger firms across years

year	Bidder	Target	Non-merger
1979	1,992	869	806
	5	3	3,931
1980	2,831	573	870
	40	24	7,553
1981	1,510	396	951
	105	53	6,880
1982	1,205	500	1,080
	176	41	7,010
1983	1,136	523	1,131
	261	55	7,791
1984	1,527	761	804
	264	85	11,034
1985	2,150	1,025	783
	83	101	12,196
1986	2,446	380	860
	116	124	12,430
1987	4,294	639	917
	112	114	12,045
1988	5,052	1,179	1,023
	109	116	12,186
1989	4,064	529	1,075
	155	102	12,702
1990	3,518	2,342	1,173
	114	74	12,644
1991	1,981	251	1,268
	180	61	12,440
1992	3,060	609	1,313
	183	57	12,468
1993	2,248	453	1,393
	187	84	12,699
1994	2,411	536	1,351
	234	98	13,433
1995	2,248	581	1,347
	330	143	14,068
1996	4,197	1,153	1,333
	343	139	14,864
1997	3,084	874	1,455
	374	216	15,302
1998	3,226	1,251	1,552
	361	228	15,488
1999	5,558	1,431	1,714
	355	249	15,034
2000	8,553	1,406	2,029
	280	157	13,925
2001	5,373	1,756	2,384
	218	106	13,114
2002	7,712	1,456	2,443
	184	58	12,751
2003	5,619	1,480	2,693
	234	91	12,791
2004	4,984	2,067	3,210
	204	62	11,300

indicator compares the capital resources and growth opportunities of a firm with the industry median (the indicator takes on the value one (zero) if the two-year sales growth is larger (smaller) than the industry median and the ratio of long-term debt to total assets is lower (higher) than the industry median) [3, 15, 39]. If there is a resource-growth mismatch, the firm may engage in mergers. We use *Return on Assets (ROA)* (the book value of net income before extraordinary items divided by total assets) variable to measure the match quality between bidders and targets [2, 3, 29, 33, 39].

Cash ratio, prior mergers and *industry mergers* variables measure managerial motives to protect opportunistic benefits through mergers. The *cash ratio* variable measures the ratio of cash reserves (cash and marketable securities divided by total assets). Large cash reserves enable managers to propose empire-building mergers and desist takeovers. The *prior mergers* variable (defined as the number of merger bids (received or made) in the prior two years excluding the current bid) shows the prior merger motives of the managers [5, 16, 21, 23, 32, 34, 42]. The desire to avoid risk by joining the herd may also motivate mergers. The *industry mergers* variable (the number of industry firms that made or received a bid divided by the total number of industry firms; ratio cumulated for the past two years) measures merger clustering in time and industry. Another approach to measure merger clustering in time would be to keep target, bidder and nonmerger ratios separately and perform compositional time series analysis [6], however *industry mergers* itself (which is a composition of target and bidder ratios) is not suitable for this type of analysis [14].

Mispricing of shares may affect investment decisions; hence merger decisions [38]. Two alternative hypotheses exist on whether managers use their private information about mispriced shares to act in the shareholder interests or to protect nonmonetary benefits. Eckbo et al. [13], Hansen [18], Rhoades-Kropf and Viswanathan [40] agree that managerial beliefs about stock overvaluation may motivate stock-financed mergers. At the expense of post-merger shareholders, these mergers motivated by overvaluation may aim to create long run value for pre-merger shareholders. Jensen [26] argues that managerial beliefs about stock overvaluation may motivate mergers financed with overvalued equity when managers want to generate and/or protect opportunistic benefits. Three variables, share turnover (defined as the number of traded stock shares divided by the total outstanding shares), price run-up (defined as the two-year change in stock price) and information asymmetry (defined as an indicator that is one if the market-to-book value[1] is higher than the industfry median and the firm's share turnover is lower than its industry median), are proxies for managerial motives to take advantage of its information advantage.

Artificial Neural Network and Multinomial Logistic Models

We use 10-fold cross validation method to estimate the performance of the artificial neural network and multinomial logit models. We randomly separate the data into 10-subsamples and train the models on 9 subsamples and use the results of the model to estimate bidder and target firms on the 10th subsample. We iterate this procedure for the 10 subsamples. We combine the estimation results from the 10 subsamples and arrive at the full sample results [31].

The sample is imbalanced in the target, bidder and non-merger classes. The number of non-merger quarters is almost 60 times more than the number of bidder quarters and 117 times more than the target quarters. This kind of imbalance adversely affects the performance of learning algorithms which assume a balanced class distribution [30]. To check whether multinomial logistic models predictive performance also suffers when the data is imbalanced, we ran the multinomial logistic model with no undersampling. The untabulated results indicate that the model failed to predict bidder and target candidacy (the prediction success for bidders is 0.88 and 0 percent). As a result, we use the under-sampling method to address the problem of unbalanced distribution of merger choice both in the artificial neural network and multinomial logistic models.

In the 9 training subsamples, we under-sample the classes with the higher number of elements (non-merging firm and bidder firm quarters) to the size of the minimum class (target firm quarters). In the 10th estimation subsample, we do not undertake any under-sampling as this would interfere in measuring how the models really perform out-of-sample.

[1]Market-to-book ratio is the ratio of the closing share price multiplied by the number of outstanding shares to the book value of equity.

Artificial neural networks are mathematical modeling tools which perform complex function mappings [22]. Artificial neural networks successfully represent complicated and nonlinear relationships between several input and output variables [7]. Artificial neural networks simulate the working principles of the human brain. An artificial neural network model is composed of three layers of neurons. First layer is the *input layer* in which number of neurons are equal to the number of input variables (in our case 14 variables) . The third layer is the *output layer* which has the neurons that represent the output variables (in our case 3 variables, one for target, one for bidder and one for non-merger firms). The second layer resides between these two layers and is called as the *hidden layer*. The hidden layer can be composed of single or multiple layers. In each layer, there are several neurons. The neurons in the input layer are connected to the hidden layer neurons. A network connects hidden layer neurons to the neurons in the output layer. Each of the links in this network has a weight. Training phase determines the weights of the links using the training dataset. We used MATLAB to implement the artificial neural network model. The network is a feed-forward backpropagation network with tan-sigmoid transfer function for hidden layer and linear transfer function for the output layer. We train the network using the Levenberg-Marquardt backpropagation method. Multinomial logistic models examine the influence of various variables on an unordered multinomial outcome. We used STATA to implement the multinomial logistic model.

III. Results

Artificial neural network model results

The predictive power of artificial neural network model is measured by the extent to which it correctly identifies the merger category of an (firm-quarter level) observation. Correct estimation percentage is calculated as $100 * NumModelDetectedAsClass_i/NumTotalClass_i$ where $NumModelDetectedAsClass_i$ is the number of cases the model corrrectly detects in merger class i and $NumTotalClass_i$ is the total number of cases in merger class i. We compute the correct estimation percentages of the artificial neural network model for different number of neurons in the hidden layer. Table 2 presents the average results of the 10 fold cross validation on the test dataset. The first column presents the number of nodes in the hidden layer and the following columns present target, bidder, non-merger and overall correct detection accuracy (in percentages). Target detection accuracy varies between 32.46 and 40.25, bidder detection accuracy varies between 43.76 and 51.83 and non-merger firm detection accuracy varies between 49.74 and 53.74. Table 2 shows that the ANN model with 10 nodes in the hidden layer performs better than the other models in terms of overall correct detection percentage.

Table 3 shows the classification percentages for ANN model with 10 nodes in the single hidden layer. The rows of Table 3 and Table 4 are the real identities of the observations (bidder, target, non-merger) and the columns are the estimated identities of the observations. The model correctly identifies target, bidder and non-merger firms with 40.25, 45.21 and 53.24 percent accuracy, respectively. The highest accuracy is for non-merger firms and the lowest accuracy is for target firms.

Multinomial logistic regression results

Table 2. Classification accuracy for artificial neural network models with different number of nodes

	Correct Detection Percentage			
# nodes	Target	Bidder	Non-merger	Overall
7	37.78	47.75	52.95	46.16
10	40.25	45.21	53.54	46.33
15	32.46	51.83	53.82	46.03
20	40.17	48.31	49.74	46.07
25	38.61	43.76	53.74	45.37

Table 3. Classification accuracy for artificial neural network model with 10 nodes

	Correct Detection Percentage		
Identity Estimate	Target	Bidder	Non-merger
Target	40.25	22.48	37.28
Bidder	24.92	45.21	29.86
Non-merger	28.29	18.17	53.54

Table 4. Classification accuracy for multinomial logistic regressions

Identity Estimate	Target	Bidder	Non-merger
Target	40.32	22.54	37.14
Bidder	19.91	52.20	27.89
Non-merger	24.29	19.94	55.77

Table 4 presents the results of multinomial logistic regressions of the 10 fold cross validation. Multinomial logit regressions estimate the probability of a firm proposing a bid, soliciting a bid, and neither proposing nor receiving a bid in the next quarter in the 10% of the data designated as test data in each validation fold. The estimated identity of a firm-quarter is a bidder-quarter if the probability of becoming a bidder firm is larger that the probability of becoming a target firm and non-merger firm. The estimated identity of a firm-quarter is a target-quarter if the probability of becoming a target firm is larger that the probability of becoming a bidder firm and non-merger firm. The model correctly identifies target, bidder and non-merger firms with 40.32, 52.20 and 55.77 percent accuracy respectively. Similar to results of ANN model, the highest accuracy is for non-merger firms and the lowest accuracy is for target firms.

IV. Conclusion

This paper compares the performance of artificial neural network and multinomial logistic models in predicting merger candidacy. Both models perform similarly while predicting target and non-merger firms. The multinomial logit model performs slightly better in predicting bidder firms. Multinomial logit models yield coefficient estimates that have economic meaning. Artificial neural network models work as a blackbox and do not automatically reveal coefficient estimates. This is why we conclude that multinomial logit models in our sample outperform artificial neural network models both in predictive and interpretative performance.

Multinomial logit models estimate linear models. Artificial neural network model handles non-linear relationships between the independent and dependent variables. Artificial neural network model is also powerful in handling large number of input variables and variables with interactions among each others. This study directly feeds the variables that proxy for merger motives into the multinomial and artificial neural network models. Further research that inputs a wider range of data into the artificial neural network model and allows it to explore linear and non-linear relationships in the data would prove beneficial.

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