

A Study on the Relation of Corporate Governance and Pricing for Initial Public Offerings

Chei-Chang Chiou, Sen-Wei Wang, and Yu-Min Wang

Abstract—The purpose of this study is to investigate the relationship between corporate governance and pricing for initial public offerings (IPOs). Empirical result finds that the prediction of pricing of IPOs with corporate governance added can have a rather higher degree of predicting accuracy than that of non governance added during the training and testing samples. Therefore, it can be observed that corporate governance mechanism can affect the pricing of IPOs.

Keywords—Artificial neural networks, corporate governance, initial public offerings.

I. INTRODUCTION

MOST corporations gain the capital which is needed in operation through IPOs. One importance part of the process of IPOs is the decision of making the most reasonable offer price. In Taiwan the offer price of IPOs is determined after corporations and underwriters look into many situations. Offering stocks commonly have abnormal returns and many researchers try to explain the phenomena of underpricing. A group of researchers have tried to resolve the problem of under-pricing through studying information asymmetry between investors, investors and issuing firms, and investors and underwriters, such as Beatty and Ritter [1], Grinblatt and Hwang [5], and Nanda and Yun [12]. Researches mentioned above can propose the issue of underpricing can be resolve after the problems of information asymmetry and information conveying are resolved. Corporate governance can be one way to resolve information asymmetry.

In recently years, ANNs model has originally been applied for industry but it has now been used for finance and management research such as stock price prediction, bond futures and option analysis, and bankruptcy prediction, etc. The reason that the ANNs model can be widely used in industry and business field is that this model has the ability to memorize and learn by itself as well as speed calculation function. In addition, it is designed to have an ability to spread and apply unknown samples [8]. Previous articles which discuss the ability of ANNs to predict IPOs offer price include Jain and Nag [8] and

Reber et al. [13]. Their prediction variables generally include company characteristics, financial variables, market and macroeconomics. Corporate governance mechanics are not examined to be able to benefit prediction ability. Therefore, this research follows the ANNs model by Jain and Nag [8] as a method to predict the offer price of IPOs. Jain and Nag [8], however, only considered financial ratios and market conditions as the determinants affecting IPOs' offer price. They did not investigate other determinants that affect offer price. This study involves more determinants that affect offer price, such as corporate governance, to attain a complete predicting model. Accuracy of OLS and ANNs for IPOs of corporate governance added and accuracy without corporate governance are placed into comparison in the study.

II. METHOD

A. Research Hypothesis

H1: The offer price model which has been added with corporate governance mechanism would have a smaller underpricing level than that of without corporate governance mechanism added.

H2: The ANN model predicts IPOs offer prices with more accuracy than the OLS model.

Data sources and empirical model

B. Research Period and Sample

The population of interest in this study is IPOs made at the Taiwan Stock Exchange in the period 2003-2008, totaling 353 companies.

C. Variables Measurement

1. Dependent Variables

(1) IPOs actual underpricing level (AUP)

This study adopts calculation formula of Filatochev and Bishop [4] over underpricing levels as follows:

$$AUP = (P_m - P_0) / P_0$$

P_m equals the closing price of on the day of stopping uptick for new issues (equals the closing price of the listing day after 2005/3/1, which does not have rising and falling limits). P_0 is the offer price of new issues.

(2) IPOs under-pricing level predicted by OLS model (LUP)

$$LUP = (P_m - PL) / PL$$

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Pm equals the closing price of on the day of stopping uptick for new issues (equals the closing price of the listing day after 2005/3/1, which does not have rising and falling limits). PL is the offer price of new issues predicting by the OLS model.

(3) IPOs under-pricing level predicted by ANNs model (NNUP)

This study adopts the ANNs model by Jain and Nag [8] to calculate the under-pricing levels of IPOs as follows:

$$NNUP = (Pm - Pnn) / Pnn$$

Pm equals the closing price of on the day of stopping uptick for new issues (equals the closing price of the listing day after 2005/3/1, which does not have rising and falling limits). Pnn is the offer price of new issues predicting by the ANNs model.

2. Independent Variables

(1) corporate governance mechanism

A. Board of director composition

a. board size (*Directorsize*): the measurement of this variable is the total number of end-of-year directors.

b. the proportion of independent directors (IDD): the measurement of this variable is shown as number of independent directors divided by number of board of directors.

c. the number of independent supervisors (IDS): the measurement of this variable is the number of independent supervisors.

B. Ownership Structure

a. director and supervisor ownership ratio (*Director*), block stockholder ownership ratio (*Largeholder*), and manager ownership ratio (*Manger*): this study defines insiders as directors and supervisors, larger shareholders who hold more than 5 % of stocks as well as company managers. Director and supervisor ownership ratio measurement is shown as number of holding end-of-year stocks for directors and supervisors divided by common shares outstanding. Block stockholder ownership ratio is shown as number of holding end-of-year stocks for larger shareholders who hold more than 5 % of stocks divided by common shares outstanding. Manager ownership ratio is measured as number of holding end-of-year stocks for managers divided by common shares outstanding.

b. institutional investor ownership ratio (*Foreign, Government, Bank, Otherinst*): this study defines the institutional investors as foreign institutional investors, government institutions, financial institutions and other institutions. Institutional investor ownership ratio is measured as shares institutional investor holding divided by common shares outstanding.

(2) Financial ratios

A. sales ratio (*Sales*): the measurement of this variable is calculated as 1 divided by sales.

B. capital expenditure / total assets (CAPEA): the measurement of this variable is calculated as capital expenditure divided by total assets.

C. capital expenditure / sales (CAPES): the measurement of this variable is calculated as capital expenditure divided by sales.

D. operating return on total assets (OPRA): the measurement of this variable is calculated as net income before depreciation and interest and tax divided by average assets.

E. operating return on sales (OPRS): the measurement of this variable is shown as net income divided by sales.

F. operating cash flow over total assets (OPCFA): the measurement of this variable is shown as operating cash flow divided by total assets.

G. operating cash flow over sales (OPCFS): the measurement of this variable is shown as operating cash flow divided by sales.

H. the asset turnover (ATU): the measurement of this variable is shown as sales divided by average assets.

I. debt ratio (DE): the measurement of this variable is shown as debt divided by total assets.

(3) firm characteristics

A. firm size (LNASSET): the measurement of this variable is shown as the log of total assets.

B. firm age (AGE): the measurement of this variable is shown as the time period of company's establishment.

C. industry (INDU): the method of measuring industry classification adopts a dummy variable. The electronics industry is 1 and non-electronics industry is 0.

D. the size of issue of IPOs (IPOSIZE): this research applies the gross proceeds raised at the IPOs as method of measurement.

(4) market mechanism

A. lots signing ratio (RATIO): the lots signing ratio and the level of under-pricing are in negative relationship.

B. market quotation (BULL): the measurement of this variable is

$$BULL = (Ii1 - Ii0) / Ii0$$

where Ii1 is the stock exchange capitalization weighted stock index of the closing quotation on the day of stopping uptick for new issues I; Ii0 is the stock exchange capitalization weighted stock index of the closing quotation on the day prior to IPOs for new issues.

C. distribution method (DISTR): its measurement adopts a dummy variable. One part of the bidding and the other part of the public drawing is 1; 0 are the all public drawings.

D. underwriter reputation (UWER): this study uses 1 plus market share of an underwriter and takes natural logarithm to measure this variable. Market share of an underwriter is total number of underwriting for an underwriter divided by total amount of IPOs during sampling periods.

E. accountant reputation (CPAR): measurement of this variable adopts a dummy variable. 1 represents audited by Big-4 accounting firms and 0 represents audited by non Big-4 ones.

F. listing or OTC (EXCHG): measurement of this variable adopts a dummy variable. 1 represents listing companies and 0 represents OTC companies.

Empirical model

D. Regression Model

1. Ordinary Least Square (OLS)

$$AUP = \alpha_0 DIRECTOR\% + \alpha_1 IDD + \alpha_2 IDS + \alpha_3 DIRECTOR + \alpha_4 LARGEHOLDER + \alpha_5 MANAGER + \alpha_6 FOREGIN + \alpha_7 GOVERNMENT + \alpha_8 BANK + \alpha_9 OTHERINST + \alpha_{10} SALES + \alpha_{11} CAPEA + \alpha_{12} CAPES + \alpha_{13} OPRA + \alpha_{14} OPRS + \alpha_{15} OPCFA + \alpha_{16} OPCFS + \alpha_{17} ATU + \alpha_{18} ROE + \alpha_{19} DE + \alpha_{20} LNASSET + \alpha_{21} AGE + \alpha_{22} INDU + \alpha_{23} EXCHG + \alpha_{24} IPO\% + \alpha_{25} DEP + \alpha_{26} LBDOLLAR + \alpha_{27} RATIO + \alpha_{28} BULL + \alpha_{29} DISTR + \alpha_{30} UWER + \alpha_{31} CPAR + \alpha_{32} VC + \varepsilon \quad (1)$$

2. Artificial Neural Networks (ANNs)

The feedforward backpropagation neural network is the neural network used most extensively up to today. It belongs to the supervised learning method and therefore, it is suitable for uses such as sample identification, problem sorting, application control and prediction [15]. This study, referring to Jain and Nag [8], uses the feedforward backpropagation neural networks as the neural networks research methods.

The feedforward backpropagation neural networks use gradient steepest descent, minimizing error functions [8]. The feedforward backpropagation neural networks model is shown as Figure 1.

1. Input layer: It places variables of research question into neuron and applies linear transfer function, $y=f(x)$.

2. Hidden layer: It is a non-linear transfer function. Number of hidden layer depends on the degree of complexity of research questions. One or two hidden layers would usually solve most problems. However, hidden layers' number of neuron parts have not been fully concluded [8]. Hornik et al. [7] addressed that the hidden layer of feedforward backpropagation neural network could only use one single layer to achieve result of convergence. Therefore, this study adopts a single hidden layer.

3. Output layer: It is the output variable of the result of research question. It is a linear transfer function.

Therefore, neural networks of this study adopts one hidden layer and sets up ten and eighteen neuron parts' feedforward backpropagation model, grouping samples randomly into two, one group of 2003-2005 of the trained samples and another of 2006-2008 of the testing samples. It also uses the predicting outcome of training and testing samples to compare the OLS and ANNs models so that the accuracy of pricing of IPOs could be assessed.

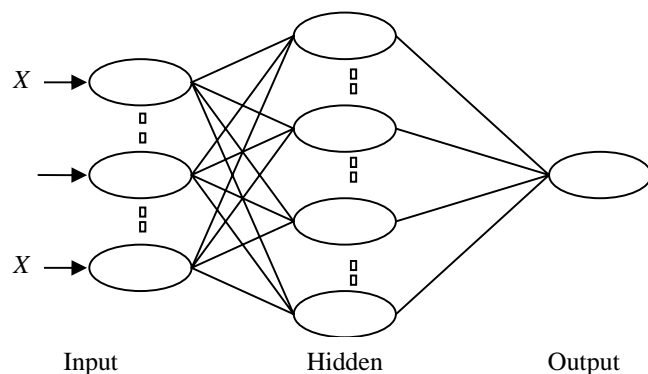


Fig. 1 Feedforward backpropagation neural networks

III. RESULTS

A. Descriptive Statistic

Table I lists the independent variables for descriptive statistics of sample companies. Within the structure of the board in corporate governance mechanism, the average value of the size of board is 6.764873 and median is 7. The mean of the proportion of independent directors on the board of directors is 0.32242 while the average number of independent supervisors is 1.022663. For ownership structure, it shows that the average values of the directors and supervisors ownership, large stockholders ownership, managers ownership, foreign investments ownership, governments ownership, banks ownership, and other corporations ownership are all above the median, which means that the distributions of these observations are all left skewness. The average values of other variables are shown in Table I.

TABLE I
 DESCRIPTIVE STATISTIC

	mean	median	Standard deviation	Max	Min
DIRECTOESIZE	6.764873	7	1.472749	12	4
IDD	0.32242	0.285714	0.096248	0.75	0
IDS	1.022663	1	0.563619	2	0
DIRECTOR	0.28467	0.254	0.142496	0.9807	0.0657
LARGEHOLDER	0.199853	0.193	0.100234	0.5595	0
MANGER	0.019341	0.0106	0.024335	0.1724	0
FOREGIN	0.057148	0.0119	0.107397	0.7774	0
GOVERNMENT	0.003037	0	0.03314	0.4515	0
BANK	0.029923	0.0069	0.059121	0.7815	0
OTHER	0.307566	0.2546	0.209348	0.9999	0
SALES	4.730923	1.425822	16.52985	236.5202	0.036479
CAPEA	0.041061	0.017119	0.068014	0.376581	-0.17788
CAPES	0.184025	0.015741	2.391745	44.93	-0.43984
ROA	0.166486	0.1585	0.106995	0.4952	-0.2479
OPRS	0.098673	0.0939	0.182432	0.525	-2.4205
OPCFA	0.080502	0.077286	0.129542	0.477496	-0.37671
OPCFS	0.09292	0.080366	0.196325	0.974591	-1.51155
ATU	1.96034	1.17	3.230233	28.01	-5.97
DE	0.377959	0.3867	0.176697	0.9099	-0.1024
LNASSET	14.33522	14.21648	1.024933	19.60904	12.38465
AGE	18.52975	17	8.754534	56	3
INDU	0.790368	1	0.407624	1	0
IPOSIZE	170.3182	67.256	398.5573	5792.1	1.66124
RATIO	0.215639	0.0324	0.345867	1	0
BULL	-0.00119	0.000363	0.019593	0.083834	-0.0966
DISTR	0.008499	0	0.091925	1	0
UWER	0.068559	0.05493	0.037425	0.126978	0.002345
CPAR	0.915	1	0.279256	1	0

EXCHG	014 0.195 467	0	0.397123	1	0
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B. Comparison of the Prediction of Pricing of IPOs for Corporate Governance-Added with Non-Corporate Governance-Added and for OLS and ANNs

The first purpose of this study is the comparison of governance added and non-governance added underpricing level of IPOs. From Table II of training samples, the result indicates that no matter in OLS or ANNs models, the governance added underpricing level (0.100196, 0.072919, 0.090891) all are smaller than non-governance added (0.210495, 0.095026, 0.119619). Therefore, from the training samples, corporate governance mechanism can improve underpricing level of IPOs.

In addition, the other purpose of this study is to compare the predictive accuracies of the OLS and ANNs models. The result explains separately the corporate governance added models and non-added models. Firstly, the corporate governance added model shows that 10 and 18 neuron parts ANNs models both have smaller underpricing (0.072919, 0.090891) than the actual underpricing level (0.097978) while the OLS model gets larger underpricing (0.100196) than the actual underpricing level (0.097978). Secondly, the corporate governance non-added model shows that although 18 neuron parts ANNs model has larger underpricing (0.119619) than the actual underpricing level (0.097978). However, the predictive accuracies of ANNs models (0.095026, 0.119619) both are better than the OLS model (0.210495). Overall, the predictive ability of the ANNs model is better than the OLS model.

In summary, for training samples, the empirical results show the adding corporate governance mechanism can improve the underpricing level of IPOs. In the predictive ability for the offer price of IPOs, the results of this study is consistent with Haefke and Helmenstein [6] and Robertson et al. [14] which indicated that the predictive ability of ANNs is better than the OLS model.

TABLE II
 THE RESULTS OF THE ACCURACIES OF IOPS OFFER PRICE-TRAINING SAMPLES

Testing samples	mean	median
AUP	0.09797 8	0.066667
Corporate governance added		
LUP	0.10019 6	0.10795
ANNUP(10)	0.07291 9	0.074185
ANNUP(18)	0.09089 1	0.099096
Corporate governance non-added		
LUP	0.21049 5	0.220853
ANNUP(10)	0.09502 6	0.109201
ANNUP(18)	0.11961 9	0.117446

From Table III of testing samples, governance added and non added are compared. The results are identical with the training samples. It indicates that the underpricing level of corporate

governance added (0.550245, 0.433141, 0.409123) are all lower than the non added (0.549822, 0.537674, 0.532831). The main reason is that companies use the independent directors and independent supervisors to supervise the company so that the underpricing situations are less by making more accurate offer prices [4,11]. Leland and Pyle [10], Certo et al. [2], Filatotchev and Bishop [4], and Chiou and Huang [3] discussed the relation of ownership structure over corporate governance and IPOs. They all indicated that the more insider ownership, manager ownership and large stockholder ownership can mean a more promising future for the company, which leads to a lower underpricing level and a stronger supervision ability through the more institutional ownership can result in a less critical situation of underpricing.

Thus, corporate governance mechanism can supervise the offer price of IPOs companies and then reduce underpricing situations. Therefore, the results correspond with the hypothesis H1; that is, governance-added models can create a smaller underpricing level than non governance added models.

The predictive accuracies of ANNs and the OLS models indicate that the underpricing levels of governance-added ANNs (0.433141, 0.409123) and OLS models (0.550245) are all smaller than actual underpricing level (0.550281). In addition, the ANNs models create more superior underpricing level than the OLS model. In the underpricing level of non governance added, the result also indicates that the underpricing level of ANNs models is smaller than the OLS model. This result corresponds with the Jain and Nag [9] and Reber et al. [13]. Therefore, hypothesis H2 can be supported.

TABLE III
 THE RESULTS OF THE ACCURACIES OF IOPS OFFER PRICE-TESTING SAMPLES

Testing samples	mean	median
AUP	0.550281	0.342432
Corporate governance added		
LUP	0.550245	0.586877
ANNUP(10)	0.433141	0.426598
ANNUP(18)	0.409123	0.39733
Corporate governance non-added		
LUP	0.549822	0.573389
ANNUP(10)	0.537674	0.541085
ANNUP(18)	0.532831	0.535319

IV. SUMMARY AND CONCLUSION

The purpose of this study is to find whether the pricing of IPOs can be affected by corporate governance mechanism. Empirical result finds that the prediction of pricing of IPOs with corporate governance added can have a rather higher degree of predicting accuracy than that of non governance added during the training and testing samples. Therefore, it can be observed that corporate governance mechanism can affect the pricing of IPOs. Secondly, the IPOs offer price predictive ability comparison of the OLS model and the ANNs model indicates that, in the testing and training of samples, the ANNs predictive ability is more superior to the OLS model.

The management implication of this study is that the corporate governance mechanism should be included into the factors which are considered for pricing agreements while companies and underwriters are together in process of agreeing offer price of IPOs. Furthermore, IPOs offer pricing can adopt the ANNs model as a pricing method.

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REFERENCES

- [1] R. P. Beatty, and J. R. Ritter, "Investment banking, reputation, and the underpricing of initial public offerings," *Journal of Financial Economics*, vol. 15, pp. 213-232, 1986.
- [2] T. S. Certo, J. G. Covin, C. M. Daily, and D. R. Dalton, "Wealth and the effects of founder management among IPO-stage new ventures," *Strategic Management Journal*, Special Issue 22, pp. 641-658, 2001.
- [3] C. C. Chiou, and Y. T. Huang, "Corporate governance and the underpricing of initial public offerings," *Commerce & Management Quarterly*, vol.8, pp. 369-391, 2007.
- [4] I. Filatotchev, and K. Bishop, "Board composition, share ownership, and 'underpricing' of U.K. IPO firms," *Strategic Management Journal*, vol. 23, pp. 941-955, 2002.
- [5] M. Grinblatt, and C. Y. Hwang, "Signaling and the pricing of new issues," *Journal of Finance*, vol. 44, pp. 393-420, 1989.
- [6] C. Haefke, and C. Helmenstein, "Forecasting Austrian IPOs: An application of linear and neural network error correction model," *Journal of Forecasting*, vol. 15, pp. 237-251, 1996.
- [7] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Network*, vol. 2, pp. 359-366, 1989.
- [8] B. A. Jain, and B. N. Nag, "Artificial neural network models for pricing initial public offerings," *Decision Science*, vol. 26, pp. 283-302, 1995.
- [9] B. A. Jain, and B. N. Nag, "A neural network model to predict long-run operating performance of new ventures," *Annals of Operations Research*, vol. 78, pp. 83-110, 1998.
- [10] H. E. Leland, and D. H. Pyle, "Information asymmetries, financial structure and financial intermediation," *Journal of Finance*, vol. 32, pp. 371-387, 1977.
- [11] T. H. Lin, "Underpricing and corporate governance evidence from Taiwan securities market," *Corporate ownership and control*, vol. 4, pp. 69-73, 2006.
- [12] V. Nanda, and Y. Yun. "Reputation and financial intermediation: An empirical investigate of the impact of IPO mispricing on underwriter market value," *Journal of Financial Intermediation*, vol. 6, pp. 39-63, 1997.
- [13] P. Reber, B. Berry, and S. Toms, "Predicting mispricing of initial public offerings," *Intelligent System in Accounting, Finance and Management*, vol. 13, pp. 41-59, 2005.
- [14] Roberston, S. J., B. L. Golden, G. C. Runger, and E. A. Wasil. 1998. Neural network models for initial public offerings. *Neurocomputing*, 18, 165-182.
- [15] Y. Yoon, G. Swales, and T. M. Margavio, "A comparison of discriminant analysis versus artificial neural networks," *Journal of Operational Research Society*, vol. 44, pp. 51-60, 1993.