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A comparison of neural network and multiple regression analysis in modeling capital structure

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Abstract

Empirical studies of the variation in debt ratios across firms have used statistical models singularly to analyze the important determinants of capital structure. Researchers, however, rarely employ non-linear models to examine the determinants and make little effort to identify a superior prediction model. This study adopts multiple linear regressions and artificial neural networks (ANN) models with seven explanatory variables of corporation's feature and three external macro-economic control variables to analyze the important determinants of capital structures of the high-tech and traditional industries in Taiwan, respectively. Results of this study show that the determinants of capital structure are different in both industries. The major different determinants are business-risk and growth opportunities. Based on the values of RMSE, the ANN models achieve a better fit and forecast than the regression models for debt ratio, and ANNs are cable of catching sophisticated non-linear integrating effects in both industries. It seems that the relationships between debt ratio and independent variables are not linear. Managers can apply these results for their dynamic adjustment of capital structure in achieving optimality and maximizing firm's value.

Keywords: Capital structure; Multiple regression model; Artificial neural network model

1. Introduction

Regarding the qualitative aspects of capital formation within the high-tech industry of the 90s, we find that beginning about 1995 a mob mentality set in within the investment community. Essentially, no rational reason could be quantified for the ability of the high-tech companies to attract large amounts of investment capital. That is, on the surface, there seemed to be an irrational behavior within the investment community. If we mine the information deeper, it would be quite rational for the venture capitalists to fund the high-tech to the extent that they did. Examining the phenomenon of the high-tech, several factors come into play. Firstly, the general economy was doing well and the allure of high-tech business was irresistible to stock purchasers. Secondly, the thought that much of the world business would be internet/computer orientated took root and became the glamorous hot issue of the day. Venture capitalist read the fervor and proceeded to fund startup companies in record numbers. As a result, the capital structure of the high-tech industry seems to be significantly different from that of the traditional industry.

Ever since Myers article (1984) on the determinants of corporate borrowing, literature on the determinants of capital structure has grown steadily. Part of this literature materialized into a series of theoretical and empirical studies whose objective has been to determine the explanatory factors of capital structure. The article of Titman and Wessels (1988) on the determinants of capital structure choice take such attributes of firms as asset structure, non-debt tax shields, growth, uniqueness, industries classification, size, earnings, volatility and profitability, but found only uniqueness was highly significant. But Harris and Raviv (1991) in their similar article on the subject point out that

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the consensus among financial economists is that leverage increases with fixed costs, non-debt tax shields, investment opportunities and firm size. And leverage decreases with volatility, advertising expenditure, the probability of bankruptcy, profitability and uniqueness of the product. Moh'd, Perry, and Rimbey (1998) employ an extensive time-series and cross-sectional analysis to examine the influence of agency costs and ownership concentration on the capital structure of the firm. Results indicate that the distribution of equity ownership is important in explaining overall capital structure and managers do reduce the level of debt as their own wealth is increasingly tied to the firm. Moreover, Mayer (1990) indicated that financial decisions in developing countries are somehow different. Rajan and Zingales (1995) study whether the capital structure in the G-7 countries other than the US is related to factors similar to those appearing to influence the capital structure of US firms. They find that leverage increases with asset structure and size, but decreases with growth opportunities and profitability. Again firm leverage is fairly similar across the G-7 countries. Booth, Aivazian, Demirguc-Kunt, and Maksimovic (2001) take tax rate, business-risk, asset tangibility, firm size, profitability, and market-to-book ratio as determinants of capital structure across 10 developing countries. They find that long-term debt ratios decrease with higher tax rates, size, and profitability, but increase with tangibility of assets. Again the influence of the market-to-book ratio and the business-risk variables tends to be subsumed within the country dummies. Recently, some studies have explored capital structure policies using different models on different countries (Chen, 2004; Dirk, Abe, & Kees, 2006; Fattouh, Scaramozzino, & Harris, 2006; Francisco, 2005). Furthermore, Kisgen (2006) examines credit rating and capital structure, and Jan (2005) develops a model to analyze the interaction of capital structure and ownership structure. Otherwise, in time-series test, Shyam-Sunder and Myers (1999) show that many of the current empirical tests lack sufficient statistical power to distinguish between the models. As a result, recent empirical research has focused on explaining capital structure choice by using time-series cross-sectional tests and panel data.

Though the achievement is rich, but there are few studies that evaluate the model's ability to predict. In addition, comparisons between linear and non-linear models for firm leverage with different industries are rare. Recently, artificial neural network (ANN) non-linear models have been widely used for resolving forecast problems (Altun, Bilgil, & Fidan, 2007; Hill, O'Connor, & Remus, 1996; Tseng, Yu, & Tzenf, 2002). The ANN model attempts to duplicate the processes of the human brain and nervous system using the computer. While this field originated in biology and psychology, it is rapidly advancing into other areas including business and economics (Chiang, Urban, & Baldridge, 1996; Enke & Thawornwong, 2005; etc.). The theoretical advantage of ANNs is that relationships need not be specified in advance since the method itself establishes relationships through a learning process. Also, ANNs do not require any assumptions about underlying population distributions. They are especially valuable where inputs are highly correlated, missing, or the systems are non-linear. A lot of research has been done to compare the performances of ANN and traditional statistical models (Kumar, 2005; Pao, 2006; Wang & Elhag, 2007; Zhang, 2001; etc.). Most researchers find that ANN can outperform linear models under a variety of situations, but their conclusions are not consistent with one another (Zhang & Qi, 2005).

Our focus is on answering three quantitatively oriented questions and proposing a qualitative comments in optimizing capital structure and maximizing firm value: (1) whether if the corporate financial leverage decisions differ significantly between high-tech and traditional industries; (2) whether if the determinants of the capital structure differ significantly in both industries; (3) whether if non-linear models provide better model fitting and forecasting than linear models for capital structure. The rest of the paper is organized as follows. Section 2 presents the data source, the definition of variables, and methodologies. Section 3 presents a comparative study of ANN and linear regression models and an attempt to rationalize the observed regularities. The final section contains the summary and conclusions.

2. Data source and methodology

In this study, corporations are classified into two categories: the high-tech and the traditional corporations. High-tech corporations include electronics, telecommunications, computer hardware, software, networking, information systems, and other related corporations. The rest are traditional corporations such as clothing, textile, trading, agriculture, manufacturing, etc. Leading one hundred corporations with sound financial statements are selected to create a database in each industry. Both data sets include a total of 720 firm-year panel data of public trading high-tech and traditional corporations in Taiwan from 2000 to 2005. The period from 2000 to 2004 is treated as the training period and the subsequent is the out-of-sample period for models. Each corporation contains one dependent variable and 10 independent variables. The Taiwan Economic Journal (TEJ) compiles all variables. Basic statistics are estimated to describe each variable collected and *t*-tests are conducted to determine if variables of high-tech corporations are different from that of traditional corporations.

As for regression models, we used total debt ratio (DEBT) as the response variables, and firm size (SIZE), growth opportunities (GRTH), profitability (ROA), tangibility of assets (TANG), non-debt tax shields (NDT), dividend payments (DIV), and business-risk (RISK) as explanatory variables of corporation's feature. In each model, there are three external macro-economic control variables: capital market factor (MK), money market factor (M2), and inflation level (PPI).

2.1. Multiple linear regression model

In order to test the relationship between capital structure and its determinants, the following multiple regression equation is proposed for the panel data.

$$\begin{aligned}\mathrm{DEBT}_{it} = {} & \alpha_0 + \alpha_1\mathrm{LSIZE}_{it} + \alpha_2\mathrm{GRTH}_{it} + \alpha_3\mathrm{ROA}_{it} \\ & + \alpha_4\mathrm{TANG}_{it} + \alpha_5\mathrm{NDT}_{it} + \alpha_6\mathrm{DIV}_{it} \\ & + \alpha_7\mathrm{RISK}_{it} + \alpha_8\mathrm{MK}_{it} + \alpha_9\mathrm{M2}_{it} + \alpha_{10}\mathrm{PPI}_{it} + u_{it}; \\ & i = 1,\ldots,N; t = 1,\ldots,T, \end{aligned} \tag{1}$$

where N is the number of cross sections ($N =$ the number of corporations) and T is the length of the time series for each cross section ($T =$ the number of months in time period). The following notation is used to define the variables in the empirical model:

DEBT	the total book-debt/total assets;
LSIZE	ln (asset size);
GRTH	average sales growth rate over the previous two year;
ROA	the earnings before interest and tax divided by total assets;
TANG	fixed assets/total assets;
NDT	ratio of depreciation, investment tax credit, and tax loss carry forward to total assets;
DIV	dividend payout ratio;
RISK	variance of the return on assets;
MK	rate of return of the overall stock market;
M2	annual growth rate;
PPI	producers' price index.

The estimation procedure involves two steps. In step one, each variable is normalized by subtracting its mean value and divided by its standard deviation to have zero mean value and unity variance for all variables. As a result, we will not have an intercept in our results and we can determine the relative importance of each independent variable in explaining variations of the dependent variable based on its estimated coefficient. Variance inflation factor (VIF) is estimated for each independent variable to identify causes of multicollinearity. Pending on the results of step one, model one is re-estimated in step two by deleting variables with insignificant coefficient or significant VIF value one at a time (stepwise) ($\mathrm{VIF}_j > 20$ implies that the jth independent variable is highly correlated with other independent variables of the model).

2.2. Artificial neural network model

The back-propagation (BP) neural network consists of an input layer, an output layer and one or more intervening layers, also referred to as hidden layers. The hidden layers can capture the non-linear relationship between variables. Each layer consists of multiple neurons that are connected to neurons in adjacent layers. Since these networks contain many interacting non-linear neurons in multiple layers, the networks can capture relatively complex phenomena.

A neural network can be trained by the historical data of a firm-year data set in order to capture the characteristics of this data set. A process of minimizing the forecast errors will iteratively adjust the model parameters (connection weights and node biased). For each training process, an input vector, we randomly selected from the training set, was submitted to the input layer of the network being trained. The output of each processing unit was propagated forward through each layer of the network (Liu, Kuo, & Sastri, 1995).

As shown in Fig. 1, the ANN model consists of an input layer with ten input nodes, one hidden layer consisting of h nodes, and an output layer with a single output note. The input to the ANN includes 10 variables used in the regression model. During training, a set of n pairs of input vectors and corresponding output, $(X(1), y(1)), (X(2), y(2)), \ldots, (X(n), y(n))$ is presented to the network, one pair at a time. A weighted sum of the inputs,

$$\mathrm{NET}_t = \sum_{i=1}^{N} w_{ti}x_i + b_t \tag{2}$$

is calculated at tth hidden node; w_{ti} is the weight on connection from the ith to the tth node; x_i is an input data from input node; N is the total number of input nodes ($N = 10$); and b_t denotes a bias on the tth hidden node. Each hidden node then uses a sigmoid transfer function to generate an output,

$$Z_t = [1 + \exp(-\mathrm{NET}_t)]^{-1} = f(\mathrm{NET}_t), \tag{3}$$

between 0 and 1. We then sent the outputs from each of the hidden nodes, along with the bias b_0 on the output node, to the output node and again calculated a weighted sum,

$$\mathrm{NET} = \sum_{t=1}^{h} v_t Z_t + b_0, \tag{4}$$

where h is the total number of hidden nodes; and v_t is the weight from the tth hidden node to the output node. The weighted sum becomes the input to the sigmoid transfer function of the output node. We then scaled the resulting output,

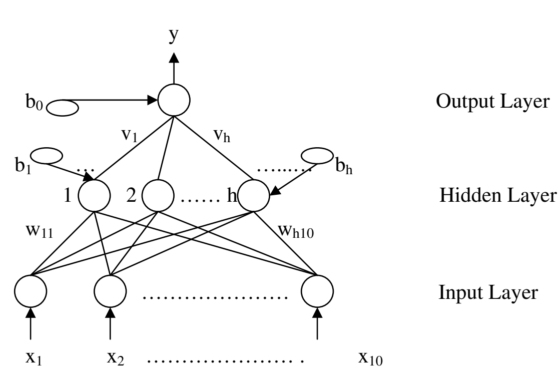

Fig. 1. Neural network model.

$$\widehat{Y} = f(\text{NET}) = [1 + \exp(-\text{NET})]^{-1}, \tag{5}$$

to provide the predicted output value. At this point, the second phase of the BP algorithm, adjustment of the connection weights, begins. The parameters of the neural network can be determined by minimizing the following objective function of SSE in the training process:

$$\text{SSE} = \sum_{j=1}^{n}(y_j - \widehat{Y}_j)^2, \tag{6}$$

where $\widehat{Y}_j$ is the output of the network for jth observation.

Assume the relationship of Y and X is monotone, then calculate the sensitivity S_i of the outputs to each of the ith inputs as a partial derivative of the output with respect to the input (Hwang, Choi, Oh, & Marks, 1991).

$$S_i = \frac{\partial \widehat{Y}}{\partial X_i} = \sum_{t=1}^{h} \frac{\partial \widehat{Y}}{\partial \text{NET}} \frac{\partial \text{NET}}{\partial Z_t} \frac{\partial Z_t}{\partial \text{NET}_t} \frac{\partial \text{NET}_t}{\partial X_i}$$
$$= \sum_{t=1}^{h}[f'(\text{NET})v_t f'(\text{NET}_t)w_{ti}]. \tag{7}$$

Assume $f'(\text{NET})$ and $f'(\text{NET})_t$ are constants and we ignore them. Then the relative sensitivity is $\widehat{S}_i = \sum_{t=1}^{h} v_t w_{ti}$. The independent variable with higher relative positive (negative) sensitivity has the higher positive (negative) impact on the dependent variable.

Performance is measured by looking at the degree to which the ANN output matches the actual value for the corresponding input values. In this study, the number of hidden nodes for the neural network was varied from one to twelve. Note that the resulting neural network models performed relatively better with six to nine hidden nodes. However, the predictive accuracy of the model improved with the in-sample data set and declined with the out-of-sample data set when more than nine hidden nodes are used. Hence, eight hidden nodes are used in the resulting ANN. In general, the need for more hidden nodes indicates big interaction of the inputs, and an enlarged ability for the neural networks to outperform other statistical models. Such a large number of hidden nodes provide assurance of the robustness of the ANN out-of-sample.

While ANNs have some limitations, several researchers have demonstrated that ANNs are excellent at developing overall models. Neural network accuracy in predicting outcomes has been documented under a wide variety of applications. This study attempts to examine the usefulness of ANNs as analyses and predictions of capital structure and to compare these ANNs with multiple linear regression results.

3. Empirical results

Table 1 presents descriptive statistics of all variables and t-tests for variable difference between high-tech and traditional corporations. The results indicate that: (1) the total debt ration, firm size, and tangibility of the high-tech corporations are insignificantly different from that of traditional corporations; (2) the growth opportunities (higher), profitability (higher), non-debt tax shield (higher), dividend policy (lower), and business-risk (higher) of the high-tech corporations are significantly different from that of the traditional corporations. Therefore, it can inferred that although the capital structure measured by debt ratio of the high-tech corporations is insignificantly different from that of the traditional corporations, the determinants of the capital structure of the high-tech corporations can be significantly different from that of the traditional corporations.

3.1. Regression results

Table 2 presents the results of standardized multiple regression models. The results indicate that: (1) all three external macro-economic variables are insignificantly associated with the capital structure for both industries; (2) the estimated VIF coefficients of all three macro-economic variables are high, i.e. VIF > 20, which would create multicollinearity to end up with inefficient estimates; and (3) the estimated root MSE are relatively high for both industries as all variables have been normalized. To improve the estimates, insignificant variables with high VIF were deleted one at a time (stepwise) and the results are presented in columns 2 and 4 of Table 3. Compare to the results of Table 3 virtually have the same implications with no statistical improvement.

3.2. ANN results

Since the results from the linear regression models are unsatisfactory, the neural network sensitivity model is employed to further analyze the possible non-linear relationship. Data during the first five years (2000–2004) served as training data, while those of the remaining last year (2005) as testing data. So, training data and testing data have 600 and 120 observations in the high-tech and traditional corporations, respectively. We adopted a back-propagation network with a {10-8-1} framework and used Eq. (7) to compute the sensitivity of each independent variable to capital structure. Table 3 lists the results.

From the results of Table 3, we conclude that: (1) ANN models have lowest RMSE values for in-sample and out-of-sample forecasting. These indicate that the non-linear ANN models generate a better fit and forecast of the panel data set than the regression model, and ANNs are cable of catching sophisticated non-linear integrating effects in both industries. It seems that the relationships between debt ratio and determinant variables are not linear. (2) Clearly on each independent variable, the sign of relative sensitivity in ANN models resembles the sign of coefficient in regression models. (3) The determinants of capital structure of the high tech industry are different from that of the traditional industry. The most important determinants (relative sensitivity greater than 1) for capital structure in high-tech

Table 1
The average of each variable in high-tech and traditional corporations

	DEBT	LSIZE	GRTH	ROA	TANG	NDT	DIV	RISK	MK	M2	PPI
HT corp.	0.45	6.71	0.26	0.10	0.31	0.10	0.28	4.68	0.19	9.01	94.27
TR corp.	0.49	6.93	0.08	0.08	0.35	0.07	0.59	2.51			
t-test	−1.12	−1.49	5.01*	3.00*	−1.45	2.83*	−3.98*	3.59*			

HT: high-tech corporation.
TR: traditional corporation.
t-test for H_0: $\mu_1 = \mu_2$ (high-tech corporation = traditional corporation).
* Significant at 5% level.

industry are, by priority, non-debt tax shields, firm size, dividend payments, business-risk; and profitability; in traditional industry are, by priority, firm size, profitability, growth opportunity, non-debt tax shields, and dividend payments. Otherwise, three macro-economic factors are insignificant on debt ratios in both industries. Based on the results of ANN models, each determinant of capital structure in both industries is discussed below.

Many previous studies (Booth et al., 2001; Harris & Raviv, 1991) argued that the capital structure might be affected by firm size positively as larger firms are more able to borrow money to realize the benefits of financial leverage. The results of this study are consistent with this presumption. Both high-tech and traditional corporations with larger size had higher debt ratio.

Myers (1977) identified growth opportunities had significant and negative impact on capital structure based on the argument that firms with higher investment in intangible assets are to use less debt to reduce the agency costs associated with risky debt. In contrary, this study found that growth opportunities had insignificant impact on capital structure for the high-tech corporations and positive and significant impact on capital structure for the traditional corporations. In combining with the results of Table 1, it seemed that most high-tech corporations are characterized by high growth opportunities (homogeneity) and therefore we could not separate and elicit the impact of high growth opportunities on capital structure statistically. Traditional corporations with higher growth opportunities had higher demand for capital to sustain their growth opportunities and borrowed more than their peers with lower growth opportunities.

Myers (1984) suggested managers have a pecking-order in which retained earnings represented the first choice, followed by debt financing, and then equity to meet their financial needs. If this is true, it would imply a negative relationship between profitability and the capital structure. The results of this study are consistent with previous studies and confirmed that both the high-tech and traditional corporations' profitability had negative impact on capital structure.

Since higher collateral value would enable firms to borrow more, previous studies suggested that firms' collateral value had a positive relationship with their capital structure. The results of this study indicated that the relationship between firms' collateral value and capital structure was positive for both the high-tech and traditional corporations. As non-debt tax shield could lower the benefit of financial leverage, previous studies suggested a negative relationship between the non-debt tax shield and the capital structure. The results of this studies confirmed that both the high-tech and traditional corporations had a negative and significant impact on capital structure. As higher cash dividend payments reflected lower capital demand, previous studies suggested that the relationship between cash dividend and capital structure should be negative. The results of this study confirmed that both the high-tech and traditional corporations had a negative relationship between cash dividend and capital structure.

In general, business-risk is a variable that includes financial distress costs. It has been supposed that firms having greater business-risk tend to have low debt ratios, as show by Bathala, Moon, and Rao (1994), Homaifar, Zietz, and Benkato (1994) and Prowse (1990). But results of this study indicate that there is a positive and significant relationship between business risk and capital structure for the high-tech corporations, but insignificant relationship for the traditional corporations. In combining with the results of Table 1, it seemed that most traditional corporations are characterized by relatively low business-risk (homogeneity) and therefore we could not separate and elicit the impact of business-risk on capital structure statistically. The business-risk is positively related to debt ratio for high-tech corporations. This is because of the attribute of high-tech industry. Generally, in high-tech industry, more speculation is associated with high risk and high investment opportunity. Firms with higher investment opportunity have higher demand for capital to sustain their investment. Therefore, business-risk is positively related to debt ratio.

4. Conclusion and further work

This paper uses standardized linear regression and non-linear ANN models with panel data to explain firm characteristics that determine capital structure in Taiwan. Results partly answers the questions posed in the introduction. It offers some hope, but also some skepticism. First, on each independent variable, the sign of relative sensitivity in ANN models resembles the sign of coefficient in regression models. And ANN models have lowest RMSE values for in-sample and out-of-sample forecasting. These indicate that the non-linear ANN models generate a better fit and

Table 2
Results of standardize multiple linear regression models

DEBT	LSIZE	GRTH	ROA	TANG	NDT	DIV	RISK	MK	M2	PPI	RMSE
High-tech	0.45 (0.14)*	0.36 (0.15)*	−0.38 (0.13)*	0.27 (0.14)	−0.72 (0.17)*	−0.16 (0.17)	0.25 (0.14)*	−0.72 (0.51)	1.75 (1.02)	−1.95 (1.31)	0.83
VIF	1.91	1.70	2.91	2.84	3.30	1.84	2.08	31.48	132.36	183.91	
Traditional	0.74 (0.12)*	0.37 (0.15)*	−0.29 (0.08)*	0.19 (0.07)*	−0.39 (0.11)*	−0.27 (0.07)*	−0.19 (0.08)*	0.20 (0.47)	−0.41 (0.71)	0.63 (0.83)	0.56
VIF	2.90	1.71	1.75	2.85	3.68	1.39	2.37	23.89	126.81	158.38	

* Significant at 5% level.

forecast of the panel data set than the regression model, and ANNs are cable of catching sophisticated non-linear integrating effects in both industries. Secondly, the empirical evidences obtained from the ANN model corroborate the following expected relationships in both industries: (1) a direct relationship between firm size and debt ratio; (2) an inverse relationship between profitability and debt; (3) an inverse relationship between non-debt tax shields and debt; and (4) an inverse relationship between dividend payments and debt. The positive coefficients on SIZE indicate that debt ratios of larger firms are less limited by the costs of financial distress, because they have more diversification than smaller firms (Smith & Watts, 1992). The negative coefficients on ROA indicate that the more profitable the firm, the lower the debt ratio. This finding is consistent with the Pecking-Order Hypothesis. It also supports the existence of significant information asymmetries. This result suggests that external financing is costly and therefore avoided by firms. However, a more direct explanation is that profitable firms have less demand for external financing, as discussed by Donaldson (1963) and Higgins (1997). This explanation would support the argument that there are agency costs of managerial discretion in high-tech industry. The negative coefficients on NDT indicate that tax deductions for depreciation and investment tax credits are substitutes for the tax benefits of debt financing. Firms with large non-debt tax shields relative to their expected cash flow include less debt in their capital structures.

Thirdly, the determinants of capital structure of high-tech industry are different from that of the traditional industry. The major different determinants are business-risk and growth opportunities. The coefficients on business-risk are positive/negative for high-tech/traditional corporations, and traditional corporations have substantially lower ratios of business-risk. This is because of the characteristic of high-tech industry. Generally, in high-tech industry, more speculation is associated with high risk and high investment opportunity. Firms with higher investment opportunity have higher demand for capital to sustain their investment. Therefore, business-risk is positively related to debt ratio. In traditional industry, business-risk is an estimate of the probability of financial distress. It notes that low business-risk enhances a firm ability to issue debt. The coefficients on growth opportunities are in-significant/positive for high-tech/traditional corporations, and traditional corporations have substantially lower growth opportunities. It seems that most high-tech corporations are characterized by high growth opportunities (homogeneity) and therefore we can not separate and elicit the impact of high growth opportunities on capital structure statistically. Traditional corporations with higher growth opportunities have higher demand for capital to sustain their growth opportunities and borrowed more than their peers with lower growth opportunities.

Finally, crucial determinants affecting capital structure in high-tech industry are, by priority, non-debt tax shields,

Table 3
Results of improve multiple regression and sensitivity from ANN

Indep. variable	High-tech		Traditional	
	Multi-reg.	ANN sensitivity	Autoreg.	ANN sensitivity
LSIZE	0.42 (0.15)*	2.48	0.81 (0.07)*	4.09
GROWTH	0.11 (0.12)	0.16	0.32 (0.06)*	1.98
ROA	−0.30 (0.14)*	−1.03	−0.36 (0.08)*	−2.86
TANG	0.28 (0.18)	0.78	0.21 (0.08)	0.85
NDT	−0.74 (0.21)*	−3.84	−0.35 (0.07)*	−1.67
DIV	−0.27 (0.14)	−2.06	−0.24 (0.10)*	−1.08
RISK	0.41 (0.15)*	1.32	−0.17 (0.06)*	−0.84
MK	N/A	−0.89	N/A	0.71
M2	N/A	0.50	N/A	−0.40
PPI	N/A	−0.27	N/A	−0.05
RMSE of out-of-sample	0.86		0.58	
RMSE of training sample		0.065		0.061
RMSE of testing sample		0.078		0.072

N/A: independent variable is deleted stepwise.
* Significant at 5% level.

firm size, dividend payments, business-risk; and profitability, in traditional industry are, by priority, firm size, profitability, growth opportunity, non-debt tax shields, and dividend payments. Otherwise, three macro-economic factors are insignificant on debt ratios in both industries.

Managers can apply these results for their dynamic adjustment of capital structure in achieving optimality and maximizing firm's value. For example, a manager may be able to enhance or reduce the benefit of financial leverage if the corporation becomes larger or profitable. Consequently, there is much that needs to be done, both in terms of empirical research as the quality of databases increases, and in developing theoretical models that provide a more direct link between profitability and capital structure choice in different industries.

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