International Journal of Applied Science and Engineering
2010. 8, 1: 47-63

Asset Write-Offs Prediction by Support Vector Machine and Logistic Regression

Chei-Wei Wu[a], Ching-Lung Chen [b], Chi-Bin Cheng[*, c]

[a] *Department of Accounting, Chaoyang University of Technology, Taiwan, R.O.C.*
[b] *Department of Accounting, National Yunlin University of Science and Technology, Taiwan, R.O.C.*
[c] *Department of Information Management, Tamkang University, Taiwan, R.O.C.*

Abstract: The purpose of asset write-offs by a firm is to provide an accurate valuation of the firm and to reveal its true business performance from the perspective of economic conditions. However, the decision to write-off assets might be manipulated by the manager of the firm and thus misguide the public to an incorrect firm value. The aim of this study is to provide quantitative prediction models for asset write-offs based on both firms' financial and managerial incentive factors. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such asset write-offs if they took place. The prediction models are constructed by support vector machine (SVM) and logistic regression for the binary decision of asset write-offs, and support vector regression (SVR) and linear regression for the write-off magnitude. The performances of different models are compared in terms of various criteria. Moreover, the bagging approach is used to reduce the variance in samples to improve prediction performance. Computational results from empirical data show the prediction performances of SVM/SVR are moderately superior to their counterpart logit/linear models. Moreover, the prediction accuracy varies with the distinctive types of asset write-offs.

Keywords: asset write-offs; support vector machine; logistic regression (Logit); bagging.

1. Introduction

The purpose of asset write-offs by a firm is to provide an accurate valuation of the firm and to reveal its true business performance from the perspective of economic conditions. The Statement of Financial Accounting Standards No.35 in Taiwan (hereafter, SFAS No. 35), published by the Financial Accounting Standards Committee of the Accounting Research and Development Foundation in July 2004 for asset impairment, states all listed companies must write-off the market value on any overvalued long-term investments, fixed assets, and other assets and record the unrealized loss in earnings in annual reports after the year 2005. Management would record asset impairments if they observe a value decline in the firm's assets below their carrying value, but they may also not report such an economic impairment if there are explicit (e.g., contractual) or implicit (e.g., perceived stock market effects) incentives. Thus, recognizing asset impairments is conceptually a

[*] Corresponding author; e-mail: cbcheng@mail.tku.edu.tw *Accepted for Publication: October 18, 2010*

function of economic factors and reporting incentives [1]. Managers have substantial flexibility over the timing, measure, and presentation of asset write-offs. Moreover, the fair value information of assets is generally difficult to obtain. Thus, whether asset write-offs are predictable and whether financial disclosures are sufficient to adequately predict asset write-offs needs to be examined. The present study aims to establish comparative quantitative prediction models for asset write-offs to enrich this stream of research.

The decision of asset write-offs is considered relevant to a firm's financial performance or economic factors[1]. Previous studies have attempted to explore the managerial incentive factors behind the asset write-offs decision[2]. Nonetheless, these studies generally focused on the timing of the asset write-offs or the factors leading to this decision. Meanwhile, these studies didn't cover an important but ignored issue: Whether asset impairments can be predicted and whether financial disclosures are sufficient to adequately predict asset impairments? Seemingly, quantitative prediction models would be more useful to investors and market participants for their ability to provide incremental information about a firm's potential recognition of an asset write-offs and the appropriate magnitude of asset impairments. There were a few studies that employed regression analysis [5, 7], logistic regression [8], or the Tobit model [8] to build an asset write-offs models. Nevertheless, they generally focused on justifying the relationship between the asset write-offs decision and the designated financial factors. The aim of this study is to establish prediction models for asset write-offs decisions. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such impairment.

Two types of approaches are used to construct the prediction models in this study; one is regression analysis in the statistical approach, and the other is the support vector machine (SVM) in the machine learning field. In the statistical approach, the logistic regression is employed to construct the binary decision model and ordinary regression analysis is used for predicting the write-off amount. In the machine learning approach, the standard SVM is used to construct the binary decision model, and the support vector regression is used for predicting the write-off amount. Performance comparisons of these two approaches are provided based on the computational results from an empirical study. Note, the empirical data demonstrates a high degree of heterogeneity; thus, the bagging technique [9] is used to improve our models' prediction performances.

2. Prediction Models

The prediction is achieved in two stages. The first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such an asset write-offs if it took place. The statistical approach (logistic regression and ordinary regression) and machine learning approach (support vector machine and support vector regression) are both employed in the two stages.

---

[1] For example, Zucca & Campbell [2], Riedl [1], Francis et al. [3], and Chao [4] documented a firm reporting asset write-offs had worse performance in terms of dividend growth rate, price earnings ratio, debts to stockholders' equity, return on assets, variances in sales revenue, operating cash flow, gross national product (GNP), and stock price.

[2] Zucca & Campbell [2], Rees et al. [5], and Healy [6] investigated the behaviors of firms that used asset write-offs to cover their earnings management intentions. Riedl [1] documented there was a significant association between write-off and "big bath" reporting behavior after the SFAS No.121 implementation. Strong & Meyer [7] and Francis et al., [3] found the change in the CEO was the most critical factor for asset write-offs decisions, especially when the new CEO was from outside the company.

2.1. Logistic regression

Logistic regression or called Logit analysis is a popular tool for binary prediction and is defined as:

$$p = \frac{\exp(\beta_0 + \beta_1 x_1 + ... + \beta_m x_m)}{1 + \exp(\beta_0 + \beta_1 x_1 + ... + \beta x_m)} \qquad (1)$$

where,

p: the probability of occurrence
x_i: explanatory variables of the prediction model, i=1,..,m
β_0: regression intercept
β_i: coefficients of the explanatory variables, i=1,..,m.

2.2. Support vector machine

Machine learning approaches, such as decision tree, case-based reasoning, and artificial neural networks (ANNs), have been widely applied to the research area of financial management. Among which, ANNs are particularly popular for constructing prediction models of financial decisions. For example, Boritz and Kennedy [10] used the backpropagation neural network for firm bankruptcy prediction; Coakley and Brown [11] reviewed the literature on ANNs applied to accounting and finance problems and suggested criteria that should be used to determine whether using an ANN is appropriate; and Cheng et al. [12] also presented a radial basis function neural network for financial distress prediction.

In recent years, a particular type of neural network known collectively as support vector machines is widely accepted as an efficient tool for prediction due to its advantages in global optimization and model generalization. The ordinary SVM [13] is a binary learning machine based on statistical learning theory. The basic idea behind SVM is to construct an optimal hyperplane as the decision surface so the margin of separation between positive and negative training examples is maximized. Those examples lying on the margins are called support vectors, generally consisting of only a small subset of the entire training examples.

The concept of binary classification was demonstrated by Cortes and Vapnik [13] as follows. In a binary classification problem, consider the training sample ($\mathbf{x}_1$, y_1),…, ($\mathbf{x}_i$, y_i), i=1,.., n, $\mathbf{x}_i \in \mathbb{R}^m$, $y_i \in \{+1, -1\}$, where $\mathbf{x}_i$ is the input pattern for the ith example and y_i is the corresponding desired class. Assuming the two classes of patterns are linearly separable, the decision surface in the form of a hyperplane that performs the separation is

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0, \qquad (2)$$

where $\mathbf{x}$ is an input vector, $\mathbf{w}$ is an adjustable weight vector, and b is a bias. The optimum hyperplane is to find the one with the maximum margin to separate the two classes of input patterns as illustrated in Figure 1. We may thus write the constraints

$$\mathbf{w}^{\mathrm{T}}\mathbf{x}_i + b \geq 1 \text{ for } y_i = +1, \qquad (3)$$

and

$$\mathbf{w}^{\mathrm{T}}\mathbf{x}_i + b \leq -1 \text{ for } y_i = -1. \qquad (4)$$

The optimum hyperplane is to maximize the margin d+ (d-) subject to constraints (3) and (4).

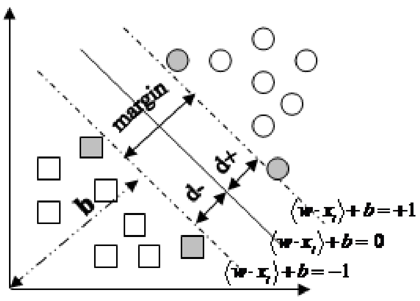

Figure 1. Optimum hyperplane for linearly separable patterns

When patterns are non-separable, it is not possible to construct a separating hyperplane without encountering classification errors. Nevertheless, we can find an optimum hyperplane that minimizes the probability of classification error by introducing slack variables ξ_i, which measure the deviation of a data point from the ideal condition of pattern separability and satisfy:

$$\mathbf{w}^{\mathrm{T}}\mathbf{x}_i + b \geq 1 - \xi_i, \text{ for } y_i = +1, \tag{5}$$

and

$$\mathbf{w}^{\mathrm{T}}\mathbf{x}_i + b \leq -1 + \xi_i, \text{ for } y_i = -1, \tag{6}$$

The function to be minimized with respect to the weight vector **w** becomes:

$$\Phi(\mathbf{w},\xi) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} + C\sum_{i=1}^{n}\xi_i \tag{7}$$

where the parameter C controls the tradeoff between the complexity of the machine and the number of non-separable points.

When data are non-linearly separable, we can map the lower dimensional input space to the higher dimensional feature space to make the data linearly separable using kernel functions. Commonly used kernel functions include inner product, polynomial, radial basis function, and sigmoid.

For regression with continuous response variable y, Vapnik [14] considered the empirical risk

$$R = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} + C\sum_{i=1}^{n}L^{\varepsilon}\left(\mathbf{x}_i, y_i, f\right) \tag{8}$$

where $L^{\varepsilon}(\mathbf{x}, y, f)$ is called Vapnik's ε-insensitive loss function [14] which is defined as

$$L^{\varepsilon}\left(\mathbf{x}, y, f\right) = \left|y - f(\mathbf{x},\mathbf{w})\right|_{\varepsilon} = \max\left(0, \left|y - f(\mathbf{x},\mathbf{w})\right| - \varepsilon\right) \tag{9}$$

where $f(\mathbf{x},\mathbf{w})$ is a function denoting the expected mean of response variable y, and ε is a measure of the diameter of a tube centering at $f(\mathbf{x},\mathbf{w})$ termed the ε-tube.

Introducing the slack variables ξ_i and $\hat{\xi}_i$, the equivalent minimization problem with respect to the weight vector **w** becomes:

Min

$$\Phi(\mathbf{w},\xi,\hat{\xi}) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} + C\sum_{i=1}^{n}\left(\xi_i + \hat{\xi}_i\right) \tag{10}$$

subject to

$$f(\mathbf{x}_i,\mathbf{w}) - y_i \leq \varepsilon + \xi_i \tag{11}$$

$$y_i - f(\mathbf{x}_i,\mathbf{w}) \leq \varepsilon + \hat{\xi}_i \tag{12}$$

$$\xi_i, \hat{\xi}_i \geq 0, \ i = 1, \cdots, n$$

where ξ_i and $\hat{\xi}_i$ measure the distance from the bounder of ε-tube.

3. Research Design

The statistical regression and SVMs presented in the previous section are employed to establish asset write-offs prediction models based on empirical data. Explanatory variables used in the models are selected from previous studies. We also determine a set of criteria to evaluate the performance of the proposed models.

3.1. Explanatory variable selection

In the first stage, we first predict whether a listed firm recognizes the requirement of asset impairments. Thus, the dependent variable is a binary variable (WO_CLASS) with the value of 1 if the listed firm recognizes asset write-offs, otherwise 0. In the second stage, we predict the magnitude of asset write-offs. Since the SFAS No.35 not only requires listed firms to write-off impaired assets when required but permits asset write-offs firms to reverse the prior impairment loss when the impaired assets recover their economic value. With the consideration of asset impairments reversals, the dependent variable of the write-off magnitude prediction model, RWOTA, is defined as follows: If a firm does not recognize asset impairments, the value of RWOTA is set to zero, and if the firm does recognize asset write-offs or perform prior write-off reversals, then RWOTA is defined as the firm's asset write-offs amount or reversing gains divided by its total assets. In the present study, we consider five types of asset write-off, namely long-term equity investment, fixed assets, goodwill, identifiable intangible assets, and other assets. Information regarding the types of asset write-offs is available in the footnotes of each firm's financial statements.

The explanatory variables of the prediction models are grouped into two categories, financial and operational variables and managerial reporting incentives variables, as discussed in the following sections.

3.1.1 Financial and operational variables

SFAS No. 35 requires management estimate the recoverable amount of the impaired assets to confirm the assets are impaired and to adjust the value of the assets based on their current positions. The asset write-offs decisions could be driven by the industry conditions, and the firm's operational conditions and asset usage capabilities. Thus, financial and operational factors are important to capture the cross-sectional variation of impairment losses. The financial/operational factors in analysis include firm size (LNASSET), returns on assets (ROA), demand for financial capital (FIN), asset turnover rate (ATR), change in asset turnover rate (△ATR), sales growth (ΔSALE), operational cash flow growth (ΔOCF), market-to-book ratio (GROWTH_OPTIONS), stock return (RET), leverage (LEVERAGE), and internal reserves of cash (CASH_RESERVES).

A prior study [15] showed large-sized firms disclosed more discretionary asset write-offs than smaller firms did in their industry. In addition to this relation, firm size is also a comprehensive variable to proxy various aspects or omitted variables of a firm. In our models, the variable of firm size (LNASSET) is measured as the logarithm of a firm's total assets at the end of the calendar year. Previous studies also showed the asset write-offs decision is related to the firm's concurrent earnings performance. Heflin and Warfield [16] pointed out managers tended to postpone asset write-offs to the year they will report poor earnings. [2,15,17] also found firms recognizing asset write-offs were generally less profitable, had earnings below expectation, or had lower returns on assets and equity in the write-off year. Accordingly, we incorporate the return on assets (ROA) variable in our prediction models.

When firms recognize asset write-offs, it will decrease concurrent earnings performance. It is found firms would not report the asset write-offs in the year it issued new securities to avoid the negative impact of poor performance on the new capital collection. We use FIN (the amount of seasonal equity and debt issuances deflated by total assets) to capture the influence of new long-term capital issuing on the firms' asset write-offs decisions. Poor usage or idle capacity of an asset would reduce its value and, to a certain extent, lead to asset impairments. Thus, two variables, assets turnover rate (ATR) and change of assets turnover rate (ΔATR), are used in the models to capture the influence of capacity usage. Smith and Watts [18] suggested high-growth firms are likely to bear more risk than mature firms do, and therefore they are more susceptible to the variation in asset values. This argument implies firms with high growth opportunity have an intrinsically risky coalition of assets and are expected to disclose a greater magnitude of write-off to reflect the expectations of future earnings from their asset combination [19]. Based on the suggestion, we used the variables of sales growth (ΔSALE) and operational cash-flows growth (ΔOCF) to capture asset recovery on an accrual basis and on a cash basis, respectively. We expect a negative relation between asset write-off magnitude and ΔSALE/Δ OCF as previously commented on by [1,18].

SFAS No. 35 states when the carrying amount of an asset is greater than its market value, it indicates possible asset impairments. In other words, if a firm's market-to-book ratio (GROWTH_OPTIONS) is less than 1, the firm's assets may be impaired. By contrast, we expect a negative relation between a firm's asset write-offs magnitude and its stock price, since stock price reflects investors' expectation of the firm's future performance. The variable stock return (RET) is used in our models to express a firm's future performance. Cotter et al. [19] argued firms with a greater capacity to absorb the financial statement effects of the asset write-offs (those with greater financial slack) are more likely to disclose larger asset impairments. We find greater financial slack is operationalized in prior studies through leverage and internal reserves of cash [2,7,17,19,20]. We thus incorporate both CASH_RESERVES and LEVERAGE variables into asset write-off prediction models to catch the influence of financial capacity on firms' asset write-offs decisions.

3.1.2 Managerial reporting motivations

Prior studies found management had considerable discretion in recognizing asset impairments and their magnitude. Zucca and Campbell [2] pointed out if a manager's objective in recognizing asset impairments is to manipulate earnings, he or she might use either the "income-smoothing" or "taking-big-baths" strategy. Murphy [21], Antle & Smith [22], and Lambert & Larcker [23] argued management's incentive plans generally tie in with reported income. If management incentive plans are based on the income-smoothing purpose, managers will do so for their personal interests. Management will selectively recognize asset impairments losses in periods with high earnings to attain the goal of income smoothing. When earnings are abnormally low, management has an incentive to "clear the deck" by recognizing assets impairment losses to signal "the worst period has already passed and the future will be bright." Two variables, BATH and SMOOTH, are used to account for the taking-big-baths tactic and the income-smoothing tactic in the prediction models, respectively, as suggested by [1]. BATH is defined as the magnitude of unexpected negative earnings[3] if earnings are lower than the median of all firms with negative earnings in the same quarter, and equals 0 otherwise. It indicates a firm has an unexpected poor earnings performance. By contrast, SMOOTH is defined as the magnitude of unexpected positive earnings if earnings are greater than the median of all firms with positive earnings in the same quarter, otherwise 0. This indicates a firm has unexpected good earnings performance. When management employs the taking-big-baths tactic to manipulate earnings, it would recognize impairment in the period of exceptionally poor earnings to "clear the deck." On the other hand, if management uses the income-smoothing tactic to manipulate earnings, it would write-off a large amount of impairment losses in the period of exceptionally good earnings performance. Further, discretionary asset write-offs are often associated with a change in top management, and are accompanied by a decrease in income in the year the change occurred [3,15,17,24]. New management has an incentive to "clear the

[3] We define unexpected earnings (ΔE) as firm's pre-impairment earnings in quarter t minus firm's earnings in quarter t-4 divided by firm's total assets at the end of quarter t-1. Unexpected negative/positive earnings are defined as unexpected earnings being less/larger than zero. We then rank all unexpected negative/positive earnings for all firms in the same period and find their median.

deck" by recognizing asset impairments losses to improve its future financial performance. To control the influences of change in top management, we incorporate two variables in our prediction models, namely △CH as changes in chairman of the board and △MD as changes in CEO. The definitions of all explanatory variables are summarized in the Appendix.

3.2. Data collection

The sample used in this study consists of the listed companies in Taiwan's stock market between 2005 and 2007. Company information and financial data are from the database of Taiwan Economic Journal Corporation (TEJ). Missing data are verified with reports published by Taiwan Stock Exchange Corporation (TSE) and Gre Tai Securities Market (OTC). The initial sample contains 1,358 firms in each year. After discarding the outliers (i.e. sample points that are 3-standard-deviations away from the mean of the concerned variables), the resulting sample consists of 1,092 firms in 2005, 1,132 firms in 2006, and 1,174 firms in 2007. Classified by year and industry, the sample data are presented in Table 1.

Table1. Distribution of firms in the sample

	2005 (N=1,092)			2006 (N=1,132)			2007 (N=1,174)		
Industry	Non-WO	WO	Total	Non-WO	WO	Total	Non-WO	WO	Total
Cement	2	5	7	2	5	7	4	3	7
Foods	11	10	21	14	7	21	12	9	21
Plastics	15	8	23	13	10	23	15	9	24
Textiles	27	23	50	33	21	54	33	20	53
Electric Machinery	53	17	70	47	25	72	52	22	74
Electric Appliance	9	5	14	8	6	14	4	10	14
Chemical & Biotech.	57	20	77	62	18	80	54	24	78
Glass & Ceramic	3	2	5	3	2	5	3	2	5
Paper Pulp	3	4	7	4	3	7	2	5	7
Iron & Steel	18	14	32	20	15	35	24	13	37
Rubber	7	4	11	8	4	12	10	2	12
Automobile	3	1	4	1	2	3	1	4	5
Electronics	441	163	604	460	169	629	468	192	660
Construction	29	20	49	25	24	49	37	14	51
Shipping	19	2	21	20	2	22	15	8	23
Tourism	10	1	11	11	1	12	11	2	13
Trade	15	3	18	14	6	20	11	8	19
Oil, Gas and Electricity	7	4	11	10	1	11	11	1	12
Others	40	17	57	30	26	56	43	16	59

Note: WO denotes asset write-off.

3.3. Empirical models

3.3.1 Statistical regression

There are 15 explanatory variables in total, as discussed earlier. The resultant model is as follows.

$$P(D\_WOTA = 1|x) = \frac{e^z}{1+e^z} \tag{13}$$

where

$$
\begin{aligned}
z_{it} &= \beta_0 + \beta_1 ROA_{it} + \beta_2 RET_{it} + \beta_3 \Delta SALE_{it} + \beta_4 \Delta OCF_{it} \\
&+ \beta_5 \Delta CH_{it} + \beta_6 \Delta MD_{it} + \beta_7 SMOOTH_{it} + \beta_8 BATH_{it} + \beta_9 FIN_{it} \\
&+ \beta_{10} GROWTH\ OPTIONS_{it} + \beta_{11} CASH\ RESERVES_{it} + \beta_{12} LEVERAGE_{it} \\
&+ \beta_{13} LNASSET_{it} + \beta_{14} ATR_{it} + \beta_{15} \Delta ATR_{it} \ + \varepsilon_{it},\ \forall i,t
\end{aligned}
$$

The amount of data is relatively scarce compared to the number of variables used in the model. Thus, only those significant variables are kept by the *both forward and backward stepwise method* when conducting an empirical analysis.

The linear regression model for asset write-offs amount prediction is presented below.

$$
\begin{aligned}
RWOTA_{it} &= \beta_0 + \beta_1 ROA_{it} + \beta_2 RET_{it} + \beta_3 \Delta SALE_{it} + \beta_4 \Delta OCF_{it} \\
&+ \beta_5 \Delta CH_{it} + \beta_6 \Delta MD_{it} + \beta_7 SMOOTH_{it} + \beta_8 BATH_{it} + \beta_9 FIN_{it} \\
&+ \beta_{10} GROWTH\ OPTIONS_{it} + \beta_{11} CASH\ RESERVES_{it} + \beta_{12} LEVERAGE_{it} \\
&+ \beta_{13} LNASSET_{it} + \beta_{14} ATR_{it} + \beta_{15} \Delta ATR_{it} \ + \varepsilon_{it},\ \forall i,t
\end{aligned} \tag{14}
$$

Similarly, the *both forward and backward stepwise method* is also used to select the most important variables to be included in the linear regression model.

3.3.2. SVMs

Since noise is intrinsic in the sample, the present study adopts the soft classification C-SVM [13] to conduct the binary prediction with parameter C to regulate the tolerance of noise. The radial basis function (RBF) is used as the kernel function in our C-SVM model. The values of C and the kernel width σ of the kernel function are determined by the grid search and cross-validation technique. We follow the suggestion of Hsu et al. [25] to set their values in the sequence of $C = 2^{-5}, 2^{-3}, \ldots, 2^{15}$ and $\sigma = 2^{-15}, 2^{-13}, \ldots, 2^{3}$, and to find their optimum in each round of learning.

The prediction of asset write-offs magnitude is obtained using the ε-SVR regression model. The value of ε is determined based on the method of Cherkassky & Ma [26], i.e., set the initial range of ε then again, find its value by the cross-validation technique. The RBF is also used as the kernel function of this model. Thus, the same techniques used in our C-SVM to determine C and σ are also used for ε-SVR.

3.3.3. Bagging

To reduce the prediction variances of the models, we use the bagging method to construct the prediction models. Let M denote a general model, i.e., Logit or SVM, $S=(x_i, y_i)$, $i=1,\ldots,N$ be N pairs of input-output data. The steps of the bagging method are as follows.

Step 1. Bootstrap
  Number of training times = T
  For j=1 to T
  Randomly draw N pieces of data with replacement from S to form a sample S_j
  Training M with S_j to obtain a trained model M_j
  Next j
Step 2. Bagging
  Let **x** be the input vector.
  Case of binary prediction:
   The final prediction with **x** is determined by a majority voting
   $M_{\text{Bagging}}(\mathbf{x}) = \text{argmax}_k \{C_k\}$, $k \in \{0, 1\}$,
   where C_k is the number of M_j whose prediction is class k for a given input **x**.
  Case of write-off magnitude prediction:

$$M_{\text{Bagging}}(\text{x}) = \frac{1}{T}\sum_{j=1}^{T} M_j(\text{x})$$

3.3.4. Prediction performance criteria

The performance evaluation of the binary prediction is based on the prediction error rate, i.e., the ratio of number of error prediction to the total number of firms in the prediction sample. The prediction error rate must be less than the random error, i.e., the number of asset write-offs firms divided by the total number of firms in the sample, for the prediction models to be effective.

The performance criteria for asset write-offs magnitude prediction include the mean squared error (MSE), the normalized mean squared error (NMSE), which reduces the effect of the scale of response variable, as suggested by Reber et al. [27], and the mean absolute percentage error (MAPE) [28]. MSE, NMSE, and MAPE can measure the difference between the actual write-off magnitudes and the predicted ones. The lower these values, the more accurate the prediction models are. MSE, NMSE, and MAPE are defined as:

$$\text{MSE} = \frac{\sum_{i=1}^{n}(A_i - F_i)^2}{n} \tag{15}$$

where n is the number of firms in the prediction sample, A_i is the actual write-off amount of the i-th firm, and F_i is its prediction by the prediction models; and

$$\text{NMSE} = \frac{\sum_{i=1}^{n}(A_i - F_i)^2}{n\delta^2} \tag{16}$$

Where

$$\delta^2 = \frac{\sum_{i=1}^{n}(A_i - \overline{A})^2}{n-1} \quad \text{and} \quad \text{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|}{n} \tag{17}$$

4. Empirical Result Analysis

In the sample, the ratios of total asset write-offs amount to total assets are 0.35%, 0.18%, and 0.13% in year 2005, 2006, and 2007, respectively. These figures indicate a low write-off ratio in industries. The descriptive statistics of all variables are provided in Table 2.

Table 2. Descriptive statistics of variables

	Mean	Standard deviation	Min	Q1	Median	Q3	Max
Panel A: 2005 (N=1,092)							
D_WOTA	0.2958	0.4566	0.0000	0.0000	0.0000	1.0000	1.0000
RWOTA	0.0035	0.0103	-0.0012	0.0000	0.0000	0.0009	0.0894
ROA	0.0567	0.0962	-0.3792	0.0133	0.0579	0.1101	0.4152
RET	0.1238	0.5021	-0.7881	-0.2087	0.0186	0.3263	2.9416
△SALSE	0.0526	0.2330	-0.8121	-0.0517	-0.0517	0.1218	1.3752
△OCF	0.0229	0.1125	-0.3550	-0.0400	-0.0400	0.0802	0.6959
△MD	0.1410	0.3482	0.0000	0.0000	0.0000	0.0000	1.0000
△CH	0.0641	0.2450	0.0000	0.0000	0.0000	0.0000	1.0000
SMOOTH	0.0205	0.0482	0.0000	0.0000	0.0000	0.0000	0.3438
BATH	-0.0205	0.0444	-0.2235	0.0000	0.0000	0.0000	0.0000
FIN	0.0129	0.0396	-0.0842	0.0000	0.0000	0.0000	0.2603
GROWTH OPTIONS	1.3960	0.8913	0.2500	0.7600	1.1550	1.7600	6.4200
CASH RESERVES	0.1286	0.1237	0.0003	0.0399	0.0905	0.1748	0.7621
LEVERAGE	0.4089	0.1716	0.0155	0.2777	0.4066	0.5174	0.9599
LNASSET	14.9400	1.2437	12.1500	14.0000	14.8200	15.7000	19.1900
ATR	0.9019	0.5593	0.0000	0.5300	0.7900	1.1400	3.4700

△ATR	-0.0529	0.8414	-5.9000	-0.4400	0.0000	0.3700	3.1000
Panel B: 2006 (N=1,132)							
D_WOTA	0.3065	0.4613	0.0000	0.0000	0.0000	1.0000	1.0000
RWOTA	0.0018	0.0062	-0.0339	0.0000	0.0000	0.0005	0.0649
ROA	0.0780	0.1377	-0.3513	0.0257	0.0700	0.1252	3.3453
RET	0.4238	0.5707	-0.6490	0.0242	0.2975	0.6769	3.0954
△SALSE	0.0783	0.2506	-0.7942	-0.7942	0.0372	0.1668	1.3211
△OCF	-0.0025	0.1122	-0.4446	-0.4446	-0.0009	0.0543	0.5704
△MD	0.1263	0.3324	0.0000	0.0000	0.0000	0.0000	1.0000
△CH	0.0565	0.2311	0.0000	0.0000	0.0000	0.0000	1.0000
SMOOTH	0.0301	0.0586	0.0000	0.0000	0.0000	0.0543	0.3708
BATH	-0.0120	0.0319	-0.1801	0.0000	0.0000	0.0000	0.0000
FIN	0.0223	0.0590	-0.4290	0.0000	0.0000	0.0000	0.3260
GROWTH OPTIONS	1.7560	1.1345	0.3600	1.0000	1.4100	2.1600	8.3500
CASH RESERVES	0.1295	0.1263	0.0002	0.0414	0.0857	0.1794	0.7687
LEVERAGE	0.3892	0.1740	0.0282	0.2581	0.3807	0.4994	0.9925
LNASSET	14.9900	1.2660	11.9300	14.0500	14.8400	15.7500	19.3100
ATR	0.9162	0.5799	0.0000	0.5300	0.8050	1.1600	3.4500
△ATR	-0.0024	0.9047	-5.3800	-0.4500	0.0100	0.4600	3.2000
Panel C: 2007 (N=1,174)							
D_WOTA	0.3101	0.4627	0.0000	0.0000	0.0000	1.0000	1.0000
RWOTA	0.0013	0.0045	-0.0395	0.0000	0.0000	0.0004	0.0386
ROA	0.0781	0.0886	-0.2963	0.0282	0.0719	0.1269	0.4368
RET	0.0637	0.4022	-0.8601	-0.1932	0.0019	0.2385	2.0844
△SALSE	0.0805	0.2151	-0.6616	-0.0229	0.0530	0.1562	0.9419
△OCF	0.0122	0.1103	-0.3211	-0.0467	0.0056	0.0655	0.6974
△MD	0.1320	0.3387	0.0000	0.0000	0.0000	0.0000	1.0000
△CH	0.0733	0.2607	0.0000	0.0000	0.0000	0.0000	1.0000
SMOOTH	0.0260	0.0524	0.0000	0.0000	0.0000	0.0465	0.3365
BATH	-0.0131	0.0327	-0.1886	0.0000	0.0000	0.0000	0.0000
FIN	0.0313	0.0770	-0.4254	0.0000	0.0000	0.0000	0.3946
GROWTH OPTIONS	1.6710	1.0555	0.3700	0.9400	1.3700	2.0400	6.8300
CASH RESERVES	0.1334	0.1347	0.0004	0.0377	0.0824	0.1844	0.7368
LEVERAGE	0.3672	0.1710	0.0158	0.2370	0.3558	0.4778	0.9684
LNASSET	15.0400	1.2523	11.9000	14.1300	14.9200	15.8000	19.2600
ATR	0.9215	0.5983	0.0000	0.5100	0.7900	1.1800	3.6100
△ATR	-0.0296	0.9198	-5.3300	-0.4500	-0.0200	0.4575	3.3300

Legends：Please see variable definitions in Appendix.

To obtain reliable results, the training data are randomly drawn from the sample with 50 replications. In each replication, 3/4 of the sample are used as the training data set and the remaining 1/4 is used as the test data set. Thus, each prediction model is identified 50 times with different sets of training data. The data processing and model construction are carried out with statistical software including R [29] and its related packages nnet [30], kernlab [31] and e1071 [32].

4.1. Binary prediction of asset write-offs decisions

As discussed previously, the asset write-offs decisions are also influenced by macroeconomic conditions, which are not considered in our models. To exclude this factor, prediction models are constructed for respective years. By the *both forward and backward stepwise method*, the explanatory variables reserved for the Logit model for 2005 are *ROA*, *CASH_RESERVES*, *RET*, *LNASSET*, *BATH*, and *SMOOTH*; for 2006 are *LNASSET*, *GROWTH_OPTIONS*, *ROA*, *ATR*, *RWOTA_05* (denotes the rate of asset write-offs from year 2005), *BATH*, and *SMOOTH*; and for 2007 are *LNASSET*, *RWOTA_06* (denotes the rate of asset write-offs from year 2006), *ROA*, △*ATR*, and *FIN*. For comparison purpose, the SVMs use the same set of variables of each year. Table 3 presents the prediction performance of various models.

Table 3. Performance comparison of various models

		Year 2005		Year 2006		Year 2007	
	model	Mean	SD	Mean	SD	Mean	SD
Single	Random	0.2941		0.3050		0.2904	
	Logit	0.2918	0.01371	0.3033	0.01609	0.2890	0.0133
	SVM	0.2863	0.01078	0.3130	0.00976	0.2793	0.0091
Ensemble	Logit	0.2926	0.01436	0.3033	0.01511	0.2892	0.0137
	SVM	0.2854	0.01099	0.3130	0.00995	0.2797	0.0091

As shown in Table 3, the prediction error rates of the single Logit model are 0.2918, 0.3033, and 0.2890, for years 2005, 2006, and 2007, respectively, which are all less than the random errors. The prediction error rates of the SVM model are 0.2863, 0.3130, and 0.2793 for the three respective years. Though the error rate for year 2006 is greater than the random error, the error rates for years 2005 and 2007 are both slightly less than that by the Logit model. The ensemble mode (i.e., with the bagging method) demonstrates a similar result. Though these results did not show SVM significantly outperforms the Logit model, the performance deviation of SVM was less than the Logit model, implying SVM can provide more robust prediction performance.

4.2. Predicting the magnitude of asset write-offs

Macroeconomic conditions and asset write-offs types are not included in our prediction models. To eliminate their effects, the training sample is divided by years and by types of asset write-off. The types of asset write-offs are long-term investment (R_INV), fixed assets (R_FA), and other assets (R_OA). The prediction results for years 2005, 2006, and 2007 are presented in Tables 4, 5, and 6, respectively, where the variables selected for each model by the *both forward and backward stepwise method* are noted at the bottom of the tables.

When the sample data are not divided by their asset write-offs types (i.e., all write-off firms), the performances of SVR are worse than the regression model for all years. However, when the data are divided, SVR usually outperformed the regression model, implying SVR has a better prediction performance when data heterogeneity is reduced by such a grouping.

From the performance comparisons presented in Tables 4~6, it is seen that SVR model generally performs better than the regression model in the measure of NMSE. This result implies that the performance of SVR is not affected by the value range of dependent variable, which happens to be the deficit of linear regression models. It is also noted that the effect of ensemble sampling is not significant as demonstrated in Tables 3~6. A possible reason is the number of data used in bagging the training sample is insufficient to produce a well generalized model. This argument will be further studied in our future research.

5. Conclusions

This study has established asset write-offs prediction models using two types approaches, namely regression analysis and support vector machines. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such asset write-off if one exists. In the first stage, the logistic regression and the SVM are used to construct models for predicting the binary prediction of asset write-offs, while in the second stage the linear regression and the SVR are used to predict the magnitude of asset write-offs.

The prediction models are identified by empirical data between years 2005 and 2007, and the performances of the two types of approaches are compared. The results indicate SVM slightly outperforms logistic regression in the binary prediction of asset write-offs decisions, but SVR did not perform better than linear regression in the prediction of asset write-offs magnitude. However, after dividing the sample data by their write-off types, SVR performs better than linear regression in most cases. This result may be attributed to the reduction in data heterogeneity after the write-off type classification, where SVR performs better in such situation.

Empirical results also showed that both regression and SVM models did not perform well in write-offs prediction with cross sectional sample. This may be due to the effect of discretionary treatment of data from different firms. However, each company has its own taste of asset write-off operations, e.g. tending overestimation or underestimation. Such a taste may demonstrate in the panel data of a company. In our future study, panel data analysis will be taken into account in the asset write-offs prediction process to improve the prediction accuracy. In addition, the present study aimed to investigate the applicability of SVM in the area of accounting research; thus only the traditionally used regression models are compared with SVM. Performance comparisons with other approaches will be conducted in our future study.

Acknowledge

The authors would like to thank Ms. Szu-Yin Wu for her assistance in collecting some empirical data for this study.

Table 4. Prediction of asset write-offs magnitude for year 2005

	All Write-off firms (N=323)		R_INV (N=134)		R_FA (N=116)		R_OA (N=156)	
Panel A: MSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	2.33E-04	4.96E-05	2.49E-04	1.20E-04	5.98E-04	3.24E-04	1.40E-04	6.00E-05
SVR	2.39E-04	6.00E-05	2.44E-04	1.39E-04	6.23E-04	3.52e-4	1.43E-04	7.33E-05
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	2.33E-04	4.98E-05	2.48E-04	1.23E-04	5.99E-04	3.23E-04	1.39E-04	5.98E-05
SVR	2.38E-04	6.20E-05	2.41E-04	1.35E-04	6.18E-04	3.49E-04	1.42E-04	7.16E-05
Panel B: NMSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	0.8793	0.0864	1.0820	0.3638	0.9699	0.1579	0.9185	0.1643
SVR	0.8911	0.057	0.9869	0.1864	0.9812	0.0895	0.8995	0.0956
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	0.8798	0.0858	1.061	0.3275	0.9722	0.1576	0.9050	0.1515
SVR	0.8881	0.0596	0.9809	0.2458	0.9732	0.0977	0.8966	0.08862
Panel C: MAPE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	8.223	4.063	11.860	5.128	54.880	91.179	13.260	8.312
SVR	7.376	4.021	13.930	10.082	50.640	73.142	11.340	5.873
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	8.251	4.114	11.730	5.185	55.550	92.392	13.190	8.334
SVR	7.256	4.059	13.610	9.299	49.270	71.429	11.430	6.608
All write-offs firms	RWOTA ~ LNASSET + ROA + △MD + ATR + FIN + △SALE							
R_INV:	R_INV ~ ROA + BATH + LNASSET +△MD + FIN +△SALE							
R_FA:	R_FA~LNASSET+△MD+RET + LEVERAGE							
R_OA:	R_OA ~ LNASSET + ROA + ATR + RET + CASH RESERVES + △CH +△SALE + GROWTH OPTIONS							

Table 5 Prediction of asset write-offs magnitude for year 2006

	All write-off firms (N=347)		R_INV (N=254)		R_FA (N=52)		R_OA (N=73)	
Panel A: MSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	1.01E-04	3.41E-05	9.03E-05	3.44E-05	1.78E-04	8.57E-05	3.93E-05	1.74E-05
SVR	1.06E-04	3.41E-05	9.15E-05	3.67E-05	1.70E-04	7.70E-05	3.82E-05	1.79E-05
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	1.01E-04	3.40E-05	9.09E-05	3.43E-05	1.77E-04	8.11E-05	3.94E-05	1.73E-05
SVR	1.05E-04	3.44E-05	9,12E-05	3.64E-05	1.68E-04	7.83E-05	3.84E-05	1.82E-05
Panel B: NMSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	0.9528	0.0725	0.9840	0.1146	1.222	1.227	1.197	0.5817
SVR	1.004	0.0977	0.9849	0.0521	1.078	0.775	1.119	0.3925
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	0.9546	0.0736	0.9927	0.1266	1.214	1.122	1.202	0.5968
SVR	0.9918	0.0642	0.9821	0.0513	1.024	0.562	1.121	0.3408
Panel C: MAPE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Linear model	22.330	32.310	24.530	40.117	3.959	1.705	9.078	5.788
SVR model	28.140	43.110	33.550	58.577	4.682	2.529	7.195	5.592
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Bag linear	22.610	32.835	24.620	40.217	3.772	1.738	9.139	5.745
Bag SVR	27.660	42.085	33.160	57.386	4.361	2.323	7.414	4.855

All write-off firms:	RWOTA ~ ROA + LEVERAGE + SMOOTH
R_INV:	R_INV ~ ROA + LNASSET + WOTA_05 + SMOOTH + LEVERAGE + R_INV_05
R_FA:	R_FA~ R_FA_05+ ROA+ GROWTH OPTIONS+FIN+SMOOTH+LEVERAGE+CASH RESERVES
R_OA:	R_OA ~ CASH RESERVES + LNASSET + FIN +△ATR + ROA

Table 6. Prediction of asset write-offs magnitude for year 2007

	All Write-off firms (N=366)		R_INV (N=254)		R_FA (N=46)		R_OA (N=93)	
Panel A: MSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	5.67E-05	1.65E-05	3.02E-05	8.75E-06	NA	NA	4.44E-05	2.25E-05
SVR	5.77E-05	1.76E-05	3.27E-05	1.15E-05	NA	NA	5.33E-05	3.10E-05
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regression	5.68E-05	1.65E-05	3.02E-05	8.77E-06	NA	NA	4.40E-05	2.28E-05
SVR	5.74E-05	1.74E-05	3.18E-05	1.02E-05	NA	NA	5.07E-05	2.99E-05
Panel B: NMSE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Linear model	0.9866	0.07466	0.9395	0.1162	NA	NA	1.1030	1.0414
SVR model	0.9969	0.07599	1.0210	0.3468	NA	NA	1.1400	0.6772
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Bag linear	0.987	0.07355	0.9386	0.1135	NA	NA	1.0820	1.0358
Bag SVR	0.9933	0.07505	0.9848	0.2162	NA	NA	1.0360	0.4412
Panel C: MAPE								
Single	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Linear model	6.229	1.858	7.159	2.226	NA	NA	9.595	5.263
SVR model	6.384	2.327	8.677	3.241	NA	NA	7.804	4.415
Ensemble	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Bag linear	6.208	1.857	7.164	2.207	NA	NA	9.457	5.125
Bag SVR	6.632	2.309	8.789	3.156	NA	NA	7.835	4.294

All write-off firms: RWOTA ~ LNASSET + RWOTA_06 + FIN +△OCF + ROA + BATH + GROWTH OPTIONS

R_INV: R_INV ~ LNASSET + △CH + △OCF + FIN

R_OA: R_OA ~ SMOOTH + LNASSET + ROA + R_OA_06

References

[1] Riedl, J. 2004. An examination of long-lived asset impairment. *Accounting Review*, 79: 823-852.

[2] Zucca, L. and Campbell, D. 1992. A closer look at discretionary write-downs of impaired assets. *Accounting Horizons*, 6: 30-41.

[3] Francis, J., Hanna, J., and Vicent, K. 1996. Causes and effects of discretionary asset write-offs. *Journal of Accounting Research*, 34: 117-134

[4] Chao, C. L. 2006. An examination of SFAS No. 35: Adoption timing motives, write-off. *The International Journal of Accounting Studies*, 45: 77-120.

[5] Rees, L., Gill, S., and Gore, R. 1996. An investigation of asset write-downs and concurrent abnormal accruals. *Journal of Accounting Research*, 34: 157-169.

[6] Healy, P. 1985. The effects of bonus

schemes on accounting decisions. *Journal of Accounting and Economics*, 7**:** 85-107.

[7] Strong, J. and Meyer, J. 1987. Asset write-downs: Managerial incentives and security returns. *Journal of Finance*, 42: 643-662

[8] Loh, A. L. C. and Tan, T. H. 2002. Asset write-offs – Managerial incentive and macroeconomic factors. *Abacus*, 38: 134-151.

[9] Dietterich, T. G. 2000. Ensemble methods in machine learning. Presented in *Multiple Classifier Systems: First International Workshop*, Cagliari, Italy, June 21-23, 2000 Proceedings.

[10] Boritz, J. E. and Kennedy, D. B. 1995. Effectiveness of neural network types for prediction of business failure. *Expert Systems with Applications*, 9: 503-512.

[11] Coakley, J. and Brown, C. 2002. Artificial neural networks in accounting and finance: modeling issues. *International Journal of Intelligent Systems in Accounting, Finance and Management*, 9: 119-144.

[12] Cheng, C.-B., Chen, C.-L., and Fu, C.-J. 2006. Financial distress prediction by a radial basis function network with Logit analysis learning, *Computational Mathematics and Applications*, 51: 579-588.

[13] Cortes, C. and Vapnik, V. 1995. Support vector networks. *Machine Learning*, 20: 273-293.

[14] Vapnik, V. 1995. "*The Nature of Statistical Learning Theory*". Springer.

[15] Elliott, J. and Shaw, W. 1988. Write-offs as accounting procedures to manage perceptions. *Journal of Accounting Research*, 26: 91-119.

[16] Heflin, F. and Warfield, T. 1997. "*Managerial discretion on accounting for asset write-offs*". working paper, University of Wisconsin-Madison.

[17] Chia, F. 1995. "*An investigation into the causes and effects of asset write-offs in Australia*". PhD dissertation: University of Western Australia.

[18] Smith Jr., W. and Watts, R. 1992. The investment opportunity set, corporate financing, dividend, and compensation policies. *Journal of Financial Economics*, 32: 263-292.

[19] Cotter, J., Stokes, D., and Wyatt, A. 1998. An analysis of factors influencing asset write-downs. *Accounting and Finance*, 38: 157-179.

[20] Duke, J. and Hunt, H. 1990. An empirical examination of debt covenant restrictions and accounting-related debt proxies. *Journal of Accounting and Economics*, 12: 45-63.

[21] Murphy, K. J. 1985. Corporate performance and management remuneration: An empirical analysis. *Journal of Accounting and Economics*, 7: 11-42.

[22] Antle, I. L. and Smith, A. 1986. An empirical investigation of the relative performance evaluation of corporate executives. *Journal of Accounting Research*, 24: 1-39.

[23] Lambert, R. A. and Larcker, D. F. 1987. An analysis of the use of accounting and market measures of performance in executive compensation contracts. *Journal of Accounting Research*, 25: 85-125.

[24] Moore, M. 1973. Management changes and discretionary accounting decisions. *Journal of Accounting Research*, 11: 100-107.

[25] Hsu, C. W., Chang, C. C., and Lin, C. J. 2008. "*A practical guide to support vector classification*". Available at http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf

[26] Cherkassky, V. and Ma, Y. 2004. Practical selection of SVM parameters and noise estimation for SVM regression. Neural Networks Archive, 17: 113-126.

[27] Reber, B., Berry, B., and Toms, S. 2005. Predicting mispricing of initial public offerings. *International Journal of Intelligent Systems in Accounting, Finance*

and Management, 13: 41-59.

[28] Levy, P. and Lemeshow, S. 1991. "*Sampling of Populations: Methods and Applications*". John Wiley.

[29] R Development Core Team, 2008. R: A language and environment for statistical computing, R Foundation for Statistical Computing: Vienna, Austria.

[30] Venables, W. N. and Ripley, B. D. 2002. "*Modern Applied Statistics with S*". fourth ed., Springer.

[31] Karatzoglou, A., Smola, A., Hornik, K. and Zeileis, A. 2004. Kernlab - An S4 package for Kernel methods in R. *Journal of Statistical Software*, 11: 1-20.

[32] Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D. and Weingessel, A. 2009. e1071: Misc functions of the department of statistics (e1071), TU Wien. R package version 1.5-19.