จุฬาลงกรณ์มหาวิทยาลัย
ทุนวิจัย
กองทุนรัชดาภิเษกสมโภช

รายงานผลการวิจัย
เรื่อง

ความน่าจะเป็นของการล้มละลายในประเทศไทย

โดย

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บทคัดย่อ

งานวิจัยครั้งนี้ได้ทำการศึกษาหาค่าความน่าจะเป็นของการล้มละลายโดยใช้รูปจำลอง KMV และ Logit โดยใช้กลุ่มตัวอย่างของบริษัทจดทะเบียนที่มีมูลค่าการซื้อขายสูงสุดจำนวน 100 บริษัทในช่วงปี 2535-2542 จากผลการศึกษาพบว่า ค่าความน่าจะเป็นของการล้มละลายจากรูปจำลอง KMV ของกลุ่มสถาบันการเงินสูงกว่าบริษัทในกลุ่มอุตสาหกรรม นอกจากนี้ค่าเฉลี่ยของการล้มละลายของกลุ่มสถาบันการเงินที่ประสบปัญหาและถูกสั่งปิดกิจการในช่วงปี 2540 สูงกว่าสถาบันการเงินที่มีความมั่นคงและไม่ถูกสั่งปิดกิจการ เมื่อทำการเปรียบเทียบความถูกต้องของรูปจำลองKMV และ Logit พบว่าการทำนายค่าความน่าจะเป็นของการล้มละลายจากรูปจำลอง Logit ให้ความถูกต้องมากกว่า นอกจากนี้ ในการศึกษาครั้งนี้ยังได้หาความสัมพันธ์ของผลตอบแทนในหลักทรัพย์กับค่าความเสี่ยงของการล้มละลายซึ่งพบว่านักลงทุนต้องการผลตอบแทนที่สูงขึ้นเมื่อลงทุนในหลักทรัพย์ที่มีความเสี่ยงสูงขึ้นด้วย

Project Title : An Investigation of Default Probability in Thailand

Name of the Investigator : Sunti Tirapat*

Year : September, 2001

Abstract

Using the sample of 100 most liquid companies listed in the Stock Exchange of Thailand during 1992-1999, the default probabilities from two approaches, the logit model and the KMV model, are calculated and compared. The results from the KMV model suggest that the default probabilities of financial institutions are higher than the probabilities of industrial companies. Moreover, the results from the KMV model confirm that the average default probabilities of the financial distressed firms in the 1997 financial crisis are higher than the average default probabilities of non-distressed firms. Comparing the prediction of the KMV model with the logit model, the results show that the logit model is better in terms of total prediction error and the Type I error at any cut off levels. The regression results suggest that the default probabilities of the two models have positive associations and seem to be consistent over the period of 1992-1999. Finally, the study examines whether the default probabilities have been priced. The results suggest that investors indeed do require compensations for default risk. The evidence also suggests that investors are more concerned of risk and require higher compensation for likelihood of default after the financial crisis.

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Section 1: Introduction

In the last two or three decades, there have been structural changes in business environment. There is mounting evidence that the market factors such as foreign exchange, interest rates have been much more volatile. The effects of these developments have been pronounced in recent years, showing a significant increase in bankruptcies in various countries. Recent international credit events such as the economic crisis in Asia in 1997 and the Russian debt default in 1998, caused significant bank losses. Regulators such as the Bank for International Settlements (BIS) and central banks of developed countries are in the process of amending the capital requirement rules for banks. They are making capital charges more responsive to a bank's credit exposure by setting new rules for how much capital banks must set aside to cover potential losses. The new Capital Accord, likely to be agreed within the next year, has been considered banks' own "internal" models as an alternative in calculating the capital.

These developments make the credit risk measurement and management one of the areas that have received a lot of attentions from both academics and practitioners. An important element in measuring the credit risk is the default probability, which can not be observed. The traditional technique to infer the default probability is credit scoring using the logit model. Recently, however, new techniques have been applied in this area in order to infer the probability using either public credit rating or equity price data. JP Morgan has extended the market risk measurement or value at risk (VAR) approach to the credit VAR. In this approach the key driver of the credit risk is the credit migration which can be observed from the transition matrix of the rating agencies such as Moody and Standards & Poor. The alternative approach is to use the Merton (1974), an option pricing model, in order to recover the default probability from the equity price. This approach has been marketed successfully by KMV Corporation, a San Francisco based company.

For Thailand, we have experienced the credit meltdown in the 1997 financial crisis. Since then there have not been many studies of credit risk modeling or the application of the new technique in this area. Tirapat and Nittayakasetwat (1999) have applied the logit-type model to determine the likelihood of firms' financial distress.

The limitation of the logit technique is that it requires adequate historical sample of financial distressed firms in estimating the model. This makes the logit model difficult to maintain since for Thailand after the 1998 there has been very few of default companies. In this study I investigate the use of option-based model in determining the default probability. The advantage of this type of model is that it uses the market price data that are observable in determining the likelihood of default. The default probabilities of the option approach are then compared with those of logit model. I also investigate whether the default probabilities have been accounted for or priced by investors in the Stock Exchange of Thailand.

The study is exploratory in nature and the goals are threefolds: i) To estimate default probability models for companies listed in the Stock Exchange of Thailand (SET) using the option-based model. ii) To test and compare the option-based models with a logit-type model. iii) To empirically test whether the default probability affects firm performance. The investigation of default probability models will be useful for the regulators and financial institutions in credit analysis. The fixed income fund managers will find that the model is useful in their investment decisions as well as general investors.

Using the sample of 100 most liquid listed companies on the Stock Exchange of Thailand during 1992-1999, the default probabilities from two approaches, the logit model and the option-based model, are calculated and compared. The results from the option-based model suggest that the default probabilities of financial institutions are higher than the probabilities of industrial companies. Moreover, the results from the option-based model confirm that the average default probabilities of the financial distressed firms in the 1997 financial crisis are higher than the average default probabilities of non-distressed firms. Comparing the prediction of the option model with the logit model, the results show that the logit model is better in terms of total prediction error and the Type I error at any cut off levels. The regression results suggest that the default probabilities of the two models have positive associations and seem to be consistent over the period of 1992-1999. Finally, I examine whether the default probabilities have been priced. The results suggest that investors indeed do require compensations for default risk. The evidence also suggests that investors are more concern of risk and require higher compensation for likelihood of default after the financial crisis.

The remaining of the study proceeds as follows. Section 2 summarizes the framework in calculating default probability and reviews some studies in this area. Section 3 discusses the sample and methodology. The results are reported in section 4. The summary of main findings and discussion are in Section 5.

Section 2: Literature review

Although many financial and academic institutions have advocated to develop credit risk measurement for at least two or three decades, the advance in this area has just emerged in the last four or five years. The credit risk measurement models can be divided into broad five categories: the traditional approach, the credit migration approach, the actuarial approach, the option-based or structural approach, and the reduced form approach. This section reviews these approaches with the focus on the logit-based and the option-based model that will be investigated in the next section.

Traditional Approach

The traditional approach in credit risk measurement usually includes expert systems, and credit-scoring systems. In an expert system, the credit decision is based on person's expertise, subjective judgment, and weighting of certain key factors. One of the most common expert system is the 5 "Cs" of credit: Character, Capital, Capacity, Collateral, and Conditions. Although these criterion are necessary in credit decision they are very subjective in nature. They depend mostly on the judgement of credit officers and they are difficult to aggregate them into one number.

The credit-scoring systems involve pre-identification of certain key factors that determine the probability of default and combine or weight them into a quantitative score. The most well known model of this type is Altman (1968) Z-score model, which based on the multivariate discriminant analysis technique. Since then, prediction of corporate failure has been a topic of much interest and more recent works have extended this line of research in three areas: statistical techniques, definitions of bankruptcy, and a greater variety of explanatory variables. For example, Ohlson (1980) utilize the logit and probit analysis to estimate the probability of bankruptcy. The adjustments of estimation bias resulting from oversampling, such as weights based on prior probabilities in the estimation process and optimal cut-off point, are discussed in Zmijewski (1984). The problems of pooling data due to a small number of samples are addressed in Zavgren (1983).

The second area of extension has dealt with the definitions of bankruptcy. For example, a model that distinguishes between financially distressed firms that survive and financially distressed firms that ultimately go bankrupt has been investigated. Gilbert et al.(1990) find different explanatory financial variables for these two groups of firms. In addition, a sample firm may be classified into more than two categories (bankrupt or non-bankrupt) and the classification probabilities can be estimated by the multinomial logit technique. For example, Poston et al.(1994) assigned firms into one of three groups according to each firm's financial condition: turnarounds, business failures, and survivors. They find that financial ratios are not so useful in distinguishing between financially distressed firms that are able to turn around and those that are unable to avoid failure. Johnsen and Melicher (1994), on the other hand, suggest that by using multinomial logit models, the classification errors can be significantly reduced.

The third area involves some adjustment of explanatory variables either by covering additional variables other than financial ratios or industry-adjusted ratios. For example, Hopwood et al.(1989) and Flagg et al.(1991) find that a qualified opinion is significant in distinguishing financially distressed firms. Some studies include macroeconomic variables to control for changes in the business environment. Rose et al.(1982) examine 28 business cycle indicators and find that economic conditions affect the failure process. Mensah (1983) evaluates the bankruptcy model using the specific price-level adjusted (SPL) data. The findings indicate that SPL data do not significantly improve bankruptcy prediction. Finally, Platt and Platt (1990) control for industry differences by using industry-normalizing ratios. The industry-relative framework results in stable bankruptcy models. Therefore, industrial growth has a significant effect on corporate failure. Furthermore, Platt and Platt (1991) investigate the stability and completeness of a bankruptcy model based on industry-relative ratios compared to that of unadjusted ratios.

Credit Migration Approach

This approach was introduced in 1997 by JP Morgan and its cosponsors as CreditMetrics. They extend the value at risk (VaR) framework to measure the risk of nontradable assets such as loans and privately placed bonds. The methodology uses the transition probabilities (rating migration) and the future credit spread on loan of a particular rating class to estimate the expected value of loan and its volatility over the horizon of interest. Then the value at risk under certain confidence level can be calculated as tradable securities.

The Actuarial Approach

This approach was developed by Credit Suisse Financial Products (CSFP) and marketed as "CreditRisk+". Its approach differs from the CreditMetrics in its objective and its theoretical foundation. CreditsMetrics basically estimates the VaR of a loan or loan portfolio by viewing rating upgrades and downgrades and the associated effects of spread changes in discount rate. CreditRisk+, on the other hand, views spread risk as part of market risk rather than credit risk. As a result, in any period, only two states of the world are considered– default and non-default. In other words CreditsMetrics focuses on the expected value of loans while CreditRisk+ the focus is on measuring expected losses of loans. In finance terminology, CreditMetrics can be thought of a mark-to-market model; CreditRisk+ is a default model.

Option-based Approach or Structural Approach

The model was developed based on Merton (1974) idea. Under the structural approach, we model the value of the assets and liabilities of borrowers and determine the trigger level that the firm will default is when the assets fall below liabilities. The default probability can be calibrated from observed market variables using the Black and Scholes (1973) option-pricing model. This approach relies on the assertion that in general a firm will default when its market value falls below certain exogenously given threshold level or the value of its debt and occurs only at maturity date[1].

In 1995, KMV Corporation has launched a default prediction model (the Credit Monitor Model) that produces and updates default predictions for major companies and banks that have their publicly traded. Basically the KMV Model is based conceptually the same as Merton's (1974) approach. Most of option-based models rely on one critical common assumption, namely the evolution of the firm value follows a diffusion process. Under diffusion process, a sudden drop in firm value is impossible therefore the firm never defaults unexpectedly. The validity of this implication is rather questionable: if a firm cannot default unexpectedly and if it is not currently in financial distress, its probability of default on very short-term debt is zero and thus, its short-term debt should have zero credit spreads. But the credit spreads on typical short-term bonds are much larger than zero. For example, Jones et al.(1984) document that the credit spreads on corporate bonds are generally too high to be matched by these approach. In this regard, Zhou (1997) suggests a simple flexible structural approach to valuing risky debt by modeling the evolution of the firm value as a jump-diffusion process. Under the jump-diffusion, a default can occur unexpectedly that mean default probabilities and credit spreads on very short-term debt can be larger than zero.

Reduced-Form Approach

While the structural approach provides the conceptual insights on default behavior, it is built on non-traded, unobservable quantity, and hence has questionable empirical value[2]. Alternative approach, so called the reduced-form approach, does not consider the relation between the default and firm value in explicit way. In contrast to the structural approach, this approach directly models the probability of default and the recovery rate. For example, Duffie and Singleton (1999) assume that default

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[1] Black and Cox (1976) allow default to occur when the value of the firm' assets reach certain threshold so that firms can default before they exhausts its assets. Longstaff and Schwartz (1995) develop a valuation model of risky fixed and floating rate corporate debt that incorporates both default and interest rate risk.

[2] Note that a firm will default if its value less than face value of debt at maturity date. The value the firm is unobservable but we can imply it from the equity price that can be considered as a call option.

occurs at risk-neutral hazard rate h_t at any time t, meaning roughly that the conditional risk-neutral probability at time t of default over small time interval δt, given no default before t is $h_t\delta t$.

Jarrow and Turnbull (1995) apply this approach for pricing derivative securities involving credit risk by taking as given a stochastic term structure of default-free interest rate and a stochastic maturity specific credit-risk spread. Jarrow and Yu (2001) extend the reduced-form approach to include default intensities dependent on the default of the counterparty risk.

Under the assumptions of this approach, bankruptcy occurs according to some exogenous stochastic process. The specification of this stochastic process is very flexible, allowing default to depend on a variety of economy-wide factors. For instance, Jarrow and Turnbull (1995) assume that the time to default follows an exponential distribution with a constant rate. Duffie and Singleton (1999) treats bankruptcy as the first jump time of a doubly stochastic Poisson process whose intensity depends on economy-wide factors, such as the spot interest rate or the Brownian motions driving the forward rates in the Heath et al.(1992).

The reduced-form approach seems to be flexible and tractable. However, it is not clear from the approach what the link or mechanism is between firm value and corporate default. For example, since the hazard rate of default in the reduced-form approach is modeled as an exogenous process, nobody knows what determine the "mysterious" hazard rate from this approach. Thus, the implication that firms can only default by surprise seems unrealistic.

In summary, in this section the broad perspective of the measure of the default probability has been presented. The focus of the review is on the logit-based model and the option-based model. These are the two models that will be applied to the listed companies in Thailand. The next section discusses the sample and methodology.

Section 3: Sample and Methodology

3.1 Sample

The sample consists of companies listed in the Stock Exchange of Thailand during 1992-1999, with top 100 volume trades during this period. The reason for selecting the top most traded firms is that the default probability under option-based model is derived from the market information. Hence, the option-based model may be inappropriate for the illiquid firms. The descriptive statistics of the sample are presented in Table 1. The average size of the sample is between 34.4 billion baht and 100 billion baht during 1992-1999. The average debt to equity ratio was 4.64 in 1992 and turned to negative numbers in 1997 and 1998 due to the negative net worth. The sample firms had average returns on assets (ROA) of 6.39% in 1992 and declined to –19.96% in 1997 and increased to around –6% in 1999. The list of the sample firm is shown in Appendix 1.

3.2 Methodology

3.2.1 Estimating the default probability

The Option-based Model or KMV Model

In this model, the expected default frequency (EDF) or the default probability is the likelihood that the value of a firm (V) is less than the face value of the debt. The EDF can be implied from the Black-Scholes option pricing model. Since the equity value of a firm is a call option we can state it as:

$$E = VN(d_1) - De^{-rT}N(d_2) \qquad (1)$$

and

$$d_1 = \frac{\ln(\frac{V}{D})\_(r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

Where

E = the market value of equity

D = the book value of liabilities (strike price)

V = the market value of assets

T = the time to maturity

r = the risk free interest rate

σ_V = the volatility of asset return

N(d) = the cumulative normal distribution function evaluated at d

We also know that the relationship between the volatility of asset and equity can be stated as

$$\sigma_E = \frac{N(d_1)V\sigma_V}{E} \qquad (2)$$

With (1) and (2) we can numerically solve for V and σ_V. Then using the property of normal density function, the EDF or the probability that the value of the firm is less than the liability can be computed. The KMV model also calculate the distant to default (DD) as the number of standard deviation from the expected firm value to default point. This number can be mapped to the historical default experience or assumed distributions to infer the default probability.

<u>The logit model</u>

The default probability can be estimated from the following logit model,

$$Prob\,(Y_i = 1) = \frac{1}{1+e^{-Z_i}} \qquad (3)$$

where $Z_i = a + \sum_j b_j X_{ji} + e_i$

As Y_i is assigned to be 1 if firm i is financially distressed and to be 0 if firm i is financially healthy, the probability with which firm i is classified as a financially distressed firm is given by $Prob(Y_i=1)$. Z_i is a linear function in which a and b are coefficients of variables, and e_i is an error term. Financially distressed firms are defined as firms that either i) were closed down by regulators (all the closed firms were banks and finance companies), or ii) were required by the Bank of Thailand or SET to submit restructuring plans (these companies were designated as C or SP[3] by the exchange).

X_j are financial ratios. Generally the financial ratios are taken from each element of the CAMEL framework as follows:

Capital: X_1 = book value of stockholders' equity / total assets (*SETA*)
Assets: X_2 = retained earnings / total assets (*RETA*)
Management: X_3 = operating income / net sales (*OINS*)
Earnings: X_4 = net income / total assets (*NITA*)
Liquidity: X_5 = net working capital / total assets (*WCTA*)

3.2.2 Comparing the option-based and the logit model

The prediction errors of default probabilities under the two models are compared under various cutoff point. The relation between the two models will be investigated using the simple linear regression:

$$EDF_{it} = \alpha + \beta LOGIT_{it} + \varepsilon \qquad (4)$$

where EDF and LOGIT is the probability of firm i at time t calculated from the option-based model and logit model, respectively. ε is the error term of the regression. If there is consistency between the two models we should expect the β to be positively significant.

[3] The SET posts a supervision sign of "C" (the filing for compliance) or "SP*" (the suspension or the temporary prohibition of trading until the causes of delisting are eliminated) against a listed company and the firm must submit the SET documents supporting the company's financial position.

3.2.3 Testing whether the default probability has been priced

To test whether the default probability has been priced in the market, a single market factor model will be applied:

$$E(R_{it}) = \alpha + \beta_k R_{mt} + \beta_j EDF_{it} \qquad (5)$$

where R_i is the return of security i, R_m is the market return, and EDF is the expected default frequency or the default probability from the option-based model. The null hypothesis is $\beta_j = 0$.

Section 4: Results

4.1. Option-based default probability

The default probabilities of the 100 sample firms during 1992-1999 are reported in Table 2. In this table, the sample firms are divided according to their industrial classification. The plot of the average default probabilities by sector is shown in Figure 1. It can be seen that the default probabilities of baking and finance sector are higher than the probabilities of other sectors. The real estate sector is the highest among the non-financial sectors. The default probabilities of banking, real estate, and finance and securities sector began to increase in 1997 and peaked in 1998 around 75%, 62%, and 50%, respectively. The other industrial sectors such as communication and energy their default probabilities did not increased until the 1998 and continued to increase in 1999.

Table 3 reports the average of the default probabilities of firms that defaulted and did not default in the 1997 financial crisis. The sample is also categorized into industrial firms and financial institutions (see also Figure 2). It is shown that for the financial institutions, the average default probabilities of the default and non-default groups were roughly the same during1992-1993. However, the average default probabilities of the default financial institutions had been rising drastically since 1994. The default probabilities of the non-default financial institutions began to increase in

1997. Both default probabilities of the default and non-default financial institutions peaked at almost the same level at 60% in 1998 and then declined in 1999.

For the industrial companies, the average default probability of the default companies was also higher than that of the non-default group. The trend of the default probabilities is quite different from that of financial institutions. The default probability of the non-default group increased marginally in 1997 and then rose sharply in 1998. For the default group, the probability rose significantly in 1997 and peaked in 1998 at around 56%.

4.2. Logit-based default probability

It should be noted that the parameters of the logit model are constructed based on the overall listed companies in 1997. The default probability for the 100 sample firms are then calculated and compared with those from the option-based model during the sample period. Specifically, the parameters of equation (3) are estimated by using the in-sample data: 60% of sample firms (in-sample) were used to estimate the model and the remaining 40% (out-of-sample) will be used to test the developed model. The results of the prediction ability of the model are reported in Table 4. Panel A reports the prediction ability for the whole sample while the in-sample and out-of sample results are reported in Panel B and C, respectively.

In general the total prediction error of the logit model is around 20 percent. The optimal cut off point should be around 0.20, the level that the Type I error is about the same as Type II error. It should be noted also that the overall results of the whole sample and the 60% sample estimations are quite the same. Hence, the comparisons of the logit model and the KMV model will be based on the whole sample estimation.

4.3. Comparison of the two approaches

In this section I first investigate the prediction ability of the two models using the sample 394 companies in 1997. Table 5 reports the prediction errors of the KMV model under various cut-off points. Figure 3 plots the total prediction errors (Panel A), Type I errors (Panel B), and Type II errors (Panel B), respectively, with various levels of the cut-off point. From Panel A, it can be seen that the total prediction errors of the logit model are lower than those of the KMV model for all cutoff points. Moreover, Panel B shows that the Type I errors of the logit model are significantly lower comparing with those of the KMV model. For example, at 0.5 cutoff point the Type I error of the logit model is 30% while the error of the KMV model is almost 90%. From Panel C it can be seen that the Type II errors of the logit model are higher than those of the KMV model. In particular, the errors of the KMV model are very small for the cutoff points higher than 0.5. These results suggest that the KMV model may not be a good prediction model. The default probabilities may be an indicator for the change in perception of the market and be useful as a warning indicator. The consistency between the two models over time remains to be examined.

To investigate the consistency between the two models, I concentrate on the probability of the sample of 100 most liquid firms during 1992-1999. It should be noted that the logit-based default probabilities of these firms are based on parameters from the whole-sample model. The consistency is then examined by the linear regression as stated in equation (4). The results of the estimations are reported in Table 6. Overall the β coefficients are positively statistically significant, except in the 1994. For example, for the 1992-1997 period the β is 0.1412 statistically significant at 1% confidence level. The results overall suggest that there is positive relation between the default probabilities between the two models and they seem to be consistent with each other.

4.4. Are default probabilities priced?

In this section we investigate whether investors price the default probability by including the probability in the single index return generating function. The results are reported in Table 7. From Panel A monthly returns of securities are regressed on the SET index and the probability of default (EDF) from the KMV model for the whole period (1992-1999). The coefficients of the EDF is 0.486, positively and statistically significant. This implies that the probability of default is priced by investors. The higher the default likelihood the higher the required rate of returns. Panel B and C presents the regressions for the period prior to the 1997 crisis (1992-1996) and the post crisis period (1998-1999), respectively. There are also positive associations between the default probability and the returns. It should be noted that the coefficient of the EDF for the post crisis period is more than twice as large as that of the prior crisis period, 0.992 comparing to 0.442, respectively. The evidence seems to suggest that investors are more concern of risk and require higher compensation for likelihood of default after the financial crisis.

Section 5: Conclusions

The study is exploratory in nature and the goal is to investigate the recent techniques in calculating the default probability for Thai companies. Using the sample of 100 most liquid companies listed in the Stock Exchange of Thailand during 1992-1999, the default probabilities from two approaches, the logit model and the KMV, are calculated and compared. The results from the KMV model suggest that the default probabilities of financial institutions are higher than the probabilities of industrial companies. The pattern of the default probabilities of these companies also differs over time. For the financial institutions the default probabilities have increased since 1994 and peaked in 1998 while for the default probabilities of industrial companies only increased sharply in 1997 and level off afterwards. Moreover, the results from the model confirm that the average default probabilities of the financial distressed companies are higher than the average default probabilities of non-distressed companies.

Comparing the prediction of the two models in 1997 shows that the logit model is better in terms of total prediction error and the Type I error at any cut off levels. The KMV model only outperforms on the Type II error. In addition, the regression results seem to suggest that the default probabilities of the two models have positive associations and seem to be consistent over the period of 1992-1999. Finally, to the question whether the default probabilities have been priced, the results suggest that investors indeed do require compensations for default risk. The evidence also suggests that investors are more concern of risk and require higher compensation for likelihood of default after the financial crisis.

Table 1 Descriptive Statistics for Top 100 Thai Listed Companies[1/]

		1991	1992	1993	1994	1995	1996	1997	1998	1999
Total Asset (Mil. Baht)	Max	595,803,563	666,008,672	782,870,385	898,373,473	1,035,447,886	1,155,109,053	1,408,618,771	1,266,949,114	1,182,878,203
	Min	39,916	103,678	102,629	574,213	643,014	619,668	387,937	1,205,713	1,107,775
	Median	4,013,765	6,151,539	8,916,825	13,179,114	16,981,442	19,369,904	19,017,899	15,789,133	15,875,185
	Average	29,008,943	33,829,544	40,961,454	50,974,891	62,180,612	70,678,766	93,620,548	96,796,972	95,413,596
Debt Equity Ratio	Max	21.9335	19.0077	39.4008	19.4523	15.6320	18.1129	850.0141[3/]	272.7677[5/]	291.4748[7/]
	Min	0.0035	0.0373	0.0618	0.0080	0.0037	-2.9985[2/]	-76.5374[4/]	-900,604.0203[6/]	-28.2515[8/]
	Median	2.9934	2.6448	2.5382	1.9329	2.2943	2.3155	4.7124	3.1358	2.6436
	Average	5.4618	4.6333	4.9334	4.1832	4.2189	4.2923	16.6564	-12,672.3095	9.1897
Debt Assets Ratio	Max	0.9564	0.9500	0.9752	0.9511	0.9399	1.8373	4.0270	4.5547	4.7448
	Min	0.0035	0.0360	0.0582	0.0079	0.0037	0.0048	0.0044	0.0109	0.1190
	Median	0.7496	0.7256	0.7173	0.6590	0.6964	0.7099	0.8476	0.7921	0.8179
	Average	0.6612	0.6656	0.6553	0.6298	0.6470	0.6961	0.8482	0.7935	0.8319
ROA	Max	0.3713	0.3929	0.3314	0.2637	0.2208	0.1747	0.1534	0.3890	0.5942
	Min	-0.0656	-0.0805	-1.6327	-0.1302	-0.3058	-1.1077	-3.9399	-2.3413	-1.1558
	Median	0.0233	0.0285	0.0295	0.0237	0.0185	0.0140	-0.1241	-0.0337	-0.0478
	Average	0.0422	0.0506	0.0231	0.0356	0.0261	-0.0124	-0.2451	-0.0731	-0.0853

[1/] Top 100 listed companies are calculated from the average trading volume during 19991-1999.
[2/] STAR
[3/] VNT
[4/] BBC
[5/] SGACL
[6/] BMB
[7/] LOXLEY
[8/] BMB

Table 2: Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y[1/]	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Banking									
BAY	0	0.1094	0.0424	0.0121	0.0146	0.0088	0.2096	0.9533	0.7387
BBC	1	0.9297	0.1658	0.3685	0.2322	0.0961	0.0008	na	na
BBL	0	0.3275	0.0609	0.0052	0.0080	0.0003	0.0018	0.3741	na
BMB	1	1.0000	0.1582	0.0542	1.0000	1.0000	1.0000	na	na
BOA	0	0.5772	0.1334	0.0351	0.0248	0.0324	0.0191	0.7244	0.3004
DTDB	0	0.3442	0.0743	0.0328	0.0224	0.0368	0.0968	0.6807	0.3997
FBCB	1	0.3150	0.1402	0.0227	0.0114	0.0106	0.0736	0.7726	na
IFCT	0	0.1357	0.0447	0.0214	0.0287	0.0108	0.0239	0.9543	0.6375
KTB	0	0.6657	0.1406	0.0125	0.0181	0.0018	0.0993	0.9829	0.3247
SCB	0	0.1087	0.0335	0.0056	0.0112	0.0042	0.0303	0.7448	0.9107
TFB	0	0.1545	0.0373	0.0065	0.0062	0.0000	0.0037	0.3914	0.3458
TMB	0	0.3590	0.0915	0.0182	0.0216	0.0108	0.1783	0.9861	0.6766
Average		0.4189	0.0936	0.0496	0.1166	0.1011	0.1448	0.7565	0.5417
Building& Furnishing Materials									
NTS	1	na	na	0.0098	0.0344	0.0090	0.0777	0.9967	na
SCC	0	0.0008	0.0005	0.0092	0.0009	0.0000	0.0000	0.1368	0.1970
SCCC	0	0.0117	0.0033	0.0259	0.0080	0.0006	0.0220	0.1233	0.2014
SSI	0	na	na	na	na	0.0061	0.0685	0.9378	0.6816
TPIPL	0	0.0277	0.0043	0.0042	na	0.0139	0.0399	0.9861	0.6388
Average		0.0134	0.0027	0.0123	0.0144	0.0059	0.0416	0.6361	0.4297
Chemicals and Plastics									
NPC	0	na	na	na	na	0.0167	0.0510	0.1259	0.2242
TPI	0	na	na	na	na	na	0.0020	0.4418	0.5841
VNT	0	na	na	na	na	na	0.0694	0.2666	0.3385
Average		na	na	na	na	0.0167	0.0408	0.2781	0.3823

[1/] Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 2 (Cont.): Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y[1/]	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Commerce									
LOXLEY	0	na	na	Na	na	0.0001	0.0317	na	0.5119
Communication									
ADVANC	0	na	0.0058	0.0083	0.0118	0.0017	0.0089	0.1028	0.1211
IEC	0	na	na	0.0050	0.0106	0.0060	0.0409	0.6964	0.4634
JASMIN	1	na	na	na	na	0.0001	0.0036	0.1040	0.2439
SAMART	0	na	na	na	0.0084	0.0072	0.0001	0.0915	0.5619
SATTEL	0	na	na	na	na	0.0037	0.0119	0.2897	0.2152
SHIN	0	0.0263	0.0118	0.0187	0.0134	0.0010	0.0045	0.0852	0.1424
TA	0	na	na	na	na	0.0004	0.0056	0.2051	0.2370
TATL	1	na	0.0382	na	0.0253	0.0133	0.0785	na	na
TT&T	0	na	na	na	na	0.0000	0.0375	0.3853	0.3695
UCOM	1	na	na	na	na	0.0008	0.0025	0.2265	0.3806
Average		0.0263	0.0186	0.0107	0.0139	0.0034	0.0194	0.2429	0.3039
Energy									
BANPU	0	0.0216	0.0066	0.0105	0.0057	0.0010	0.0011	0.0820	0.2272
BCP	0	na	na	na	na	0.0060	0.0153	0.3299	0.2256
EGCOMP	0	na	na	na	na	na	0.0042	0.0489	0.0574
LANNA	0	na	na	na	na	0.0044	0.0014	0.0189	0.1747
PTTEP	0	na	na	na	0.0201	0.0012	0.0014	0.0227	0.0851
SUSCO	0	0.0577	0.0668	0.0128	0.0089	0.0147	0.0223	0.3668	0.4601
Average		0.0396	0.0367	0.0116	0.0116	0.0055	0.0076	0.1448	0.2050
Electronic Components									
ATEC	1	na	na	na	0.0174	0.0021	0.0020	na	na

[1/] Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 2 (Cont.): Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y[1/]	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Entertainment and Recreation									
SAFARI	0	na	na	na	na	0.0205	0.0513	0.1770	0.1712
UBC	1	na	na	na	na	na	0.0000	0.1559	0.1081
Average		na	na	na	na	0.0205	0.0257	0.1665	0.1397
Finance and Securities									
ASL	0	na	0.0359	0.0183	0.0146	0.0432	0.0542	0.1255	0.1614
AST	0	0.0227	0.0344	0.0188	0.0212	0.0208	0.0155	0.1117	0.1517
CMIC	1	0.0763	0.0286	0.0092	0.0503	0.0626	0.1541	na	na
CNS	0	0.0353	0.0139	0.0139	0.0355	0.0367	0.0499	0.1527	na
DEFT	1	na	na	na	na	0.0305	0.1058	na	na
DS	1	0.0830	0.0310	0.0143	0.0159	0.0461	0.0415	0.6364	na
EFS	0	na	na	0.0308	0.0403	0.0354	0.0959	0.3835	0.0000
FCI	1	0.0819	0.1329	0.1203	0.0173	0.0092	1.0000	0.6931	na
FIN1	1	0.0664	0.0254	0.0134	0.0393	0.0284	0.0505	na	na
GF	1	0.0754	0.0235	0.0128	0.0568	0.0349	0.1654	na	na
ITF	1	0.0369	0.0319	0.0212	0.0282	0.0465	0.6079	na	na
KK	1	0.0683	0.0204	0.0125	0.0129	0.0738	0.1619	0.3488	0.5510
KTT	0	na	na	na	na	na	0.0463	0.6267	0.5679
NAVA	1	0.0537	0.0392	0.0102	0.0410	0.0358	0.0846	0.7569	na
NFS	0	0.0674	0.0147	0.0132	0.0456	0.0304	0.0695	0.4170	0.4474
NPAT	1	na	na	na	na	0.0152	0.1752	na	na
PHATRA	0	0.0861	0.0129	0.0096	0.0147	0.0106	0.0283	0.3729	0.6780
PRIME	1	na	na	0.0342	0.0614	0.0657	0.3183	na	na
SCCF	1	na	na	na	0.0620	na	0.5678	na	na
SDF	1	0.1013	0.0611	0.0354	0.0522	0.0980	0.6912	na	na
SGACL	0	0.0816	0.0238	0.0156	0.0545	0.0432	0.0386	0.9957	0.4074
SGF	0	0.0842	0.0410	0.0271	0.0276	0.0832	0.0802	0.7071	0.5652
SITCA	1	na	na	na	0.0925	0.0483	0.0421	na	0.0000

[1/] Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 2 (Cont.): Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y[1/]	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Finance and Securities									
S-ONE	0	0.0559	0.0183	0.0236	0.0194	0.0237	0.0380	0.4536	0.0000
SPL	0	na	na	Na	0.0211	0.0409	0.1346	0.9750	0.6406
TFS	1	na	na	0.0649	0.0788	0.0891	0.7452	na	na
TTF	1	na	0.0567	0.0173	0.0528	0.0592	0.2129	na	na
UAF	1	0.0816	0.0290	0.0099	0.0381	0.0633	0.1618	0.4864	na
UNITED	1	na	0.0427	0.0112	0.0607	0.0606	0.3818	na	na
WALL	1	na	na	Na	0.0379	0.1063	0.4294	na	na
Average		0.0681	0.0359	0.0242	0.0405	0.0479	0.2249	0.5152	0.3476
Foods and Beverages									
TC	0	0.0431	0.0170	0.0274	0.0130	0.0136	0.0522	0.1428	na
UCT	1	0.0861	0.1065	0.0372	0.0270	0.0538	Na	na	na
Average		0.0646	0.0617	0.0323	0.0200	0.0337	0.0522	0.1428	na
Health Care Services									
PYT	0	na	na	na	0.0098	0.0257	0.0010	0.4994	0.3496
Mining									
PDI	0	0.0089	0.0094	0.0119	0.0241	0.0243	0.0755	0.1528	0.0911
Others									
ONE	1	0.0959	0.0711	0.0513	0.0564	0.0247	0.0875	na	na
Packaging									
NEP	0	na	0.0576	0.0211	0.0155	0.0388	0.0641	0.5257	0.4719
Printing and Publishing									
WAT	0	na	0.0541	0.0036	0.0360	0.0013	0.0003	na	na

[1/] Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 2 (Cont.): Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y1/	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Property Development									
AMARIN	0	0.0461	0.0456	0.0121	0.0004	0.0018	0.0062	0.2086	0.3298
BCHANG	1	na	na	Na	0.0090	0.0513	0.1149	na	na
B-LAND	0	na	na	0.0131	0.0112	0.0163	0.0431	0.9870	0.6551
CK	0	na	na	Na	na	na	0.0003	0.0691	0.0744
CNTRY	1	na	na	Na	na	0.0092	0.0007	na	na
HEMRAJ	0	na	na	0.0108	0.0305	0.0071	0.0006	0.1575	0.4042
ITD	0	na	na	na	na	0.0014	0.0179	0.3242	0.2992
JULDIS	0	0.0600	0.0158	0.0039	0.0076	0.0223	0.1570	1.0000	na
KMC	1	na	0.0763	0.0127	0.0058	0.0059	0.0481	1.0000	0.7935
LH	0	0.0441	0.0045	0.0014	0.0010	0.0017	0.0056	0.3252	0.2694
MDX	0	na	na	0.0014	0.0194	0.0558	0.0448	0.8402	na
QH	0	na	0.0241	0.0227	0.0340	0.0625	0.1039	0.8044	0.5515
RR	1	0.0421	0.1147	0.0783	0.0150	0.0757	0.2292	0.8381	na
SOMPR	1	na	0.0208	0.0147	0.0507	0.1091	0.7696	na	na
STAR	1	0.0484	0.0278	0.0243	0.0159	0.0353	Na	na	na
SUPALI	0	na	na	na	0.0181	0.0558	0.0560	1.0000	0.7650
TYONG	0	na	0.0263	0.0237	0.0121	0.0191	0.0685	0.8955	0.5912
UNIVES	0	0.0397	0.0373	0.0170	0.0393	0.0248	0.1697	na	na
Average		0.0467	0.0393	0.0182	0.0180	0.0327	0.1080	0.6500	0.4733

1/ Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 2 (Cont.): Default Probability Prediction of Top 100 Thai Listed Companies during 1992-1999 using KMV Model

Companies	Y[1/]	Year							
		1992	1993	1994	1995	1996	1997	1998	1999
Pulp and Paper									
AA	0	na	na	na	na	na	0.0001	0.0646	0.1692
Textiles, Clothing, and Footwear									
CPH	0	na	na	0.0071	0.0273	0.0000	0.0000	0.2244	0.3798
SUC	0	0.0133	0.0046	0.0079	0.0069	0.0021	0.0036	0.0712	0.1581
Average		0.0133	0.0046	0.0075	0.0171	0.0011	0.0018	0.1478	0.2690
Transportation									
BECL	0	na	na	na	na	na	0.0035	0.0669	0.1458
THAI	0	na	na	0.0017	0.0073	na	0.0322	0.1405	0.1387
Average		na	na	0.0017	0.0073	na	0.0178	0.1037	0.1423

[1/] Financially distressed or bankruptcy companies are code as 1 or 0 otherwise.

Table 3: Average Default Probability from the KMV Model

	1992	1993	1994	1995	1996	1997	1998	1999
Default								
Financial Institution	0.2284	0.0658	0.0489	0.1021	0.0991	0.3260	0.6157	0.5510
(No. of Sample)	13	15	17	20	21	22	6	1
Industrial Companies	0.0681	0.0651	0.0326	0.0257	0.0300	0.1179	0.5536	0.3815
(No. of Sample)	4	7	7	10	13	12	6	4
Non-Default								
Financial Institution	0.2009	0.0502	0.0178	0.0237	0.0250	0.0657	0.6057	0.4419
(No. of Sample)	16	17	18	19	19	20	20	18
Industrial Companies	0.0308	0.0220	0.0117	0.0149	0.0130	0.0317	0.3517	0.3265
(No. of Sample)	13	18	24	27	37	44	41	39

Table 4: The Default Probability from the Logit Model

$$\Pr ob(Y_i = 1) = \frac{1}{1 + e^{-z_i}}$$

Where $Z_i = 1.76C - 9.54SETA - 5.73RETA - 0.35OINS - 9.36NITA - 0.98WCTA$

Panel A: Whole Sample [a/]

Cutoff Point	Bankruptcy Prediction				Nonbankruptcy Prediction				Total Prediction			
	Accuracy [b/]		Type I Error [c/]		Accuracy [d/]		Type II Error [e/]		Accuracy		Error	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
0.10	74	92.50%	6	7.50%	231	73.57%	83	26.43%	305	77.41%	89	22.59%
0.20	67	83.75%	13	16.25%	263	83.76%	51	16.24%	330	83.76%	64	16.24%
0.30	61	76.25%	19	23.75%	278	88.54%	36	11.46%	339	86.04%	55	13.96%
0.40	59	73.75%	21	26.25%	284	90.45%	30	9.55%	343	87.06%	51	12.94%
0.50	55	68.75%	25	31.25%	286	91.08%	28	8.92%	341	86.55%	53	13.45%
0.60	50	62.50%	30	37.50%	291	92.68%	23	7.32%	341	86.55%	53	13.45%
0.70	43	53.75%	37	46.25%	297	94.59%	17	5.41%	340	86.29%	54	13.71%
0.80	33	41.25%	47	58.75%	305	97.13%	9	2.87%	338	85.79%	56	14.21%
0.90	16	20.00%	64	80.00%	312	99.36%	2	0.64%	328	83.25%	66	16.75%
1.00	2	2.50%	78	97.50%	314	100.00%	0	0.00%	316	80.20%	78	19.80%

[a/] The Sample is divided into two subsample : 60% of the whole sample as the in-sample and 40% of the whole sample as the out-sample.
[b/] Bankruptcy prediction accuracy is code as (1,1) or a bankrupt firm(1) is correctly classified.
[c/] Type I Error is coded as (1,0) or a bankrupt firm(1) is misclassified as a nonbankrupt firm(0).
[d/] Nonbankruptcy predicton accuracy is coded as (0,0) or a nonbankrupt firm (0) is correctly classified.
[e/] Type II Error is coded as (0,1) or a nonbankrupt firm (0) is misclassified as a bankrupt firm (0).

Table 4: The Default Probability from the Logit Model

Panel B: In-sample [a/]

Cutoff Point	Bankruptcy Prediction				Nonbankruptcy Prediction				Total Prediction			
	Accuracy [b/]		Type I Error [c/]		Accuracy [d/]		Type II Error [e/]		Accuracy		Error	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
0.10	46	95.83%	2	4.17%	143	75.66%	46	24.34%	189	79.75%	48	20.25%
0.20	42	87.50%	6	12.50%	165	87.30%	24	12.70%	207	87.34%	30	12.66%
0.30	38	79.17%	10	20.83%	176	93.12%	13	6.88%	214	90.30%	23	9.70%
0.40	37	77.08%	11	22.92%	177	93.65%	12	6.35%	214	90.30%	23	9.70%
0.50	34	70.83%	14	29.17%	178	94.18%	11	5.82%	212	89.45%	25	10.55%
0.60	31	64.58%	17	35.42%	179	94.71%	10	5.29%	210	88.61%	27	11.39%
0.70	26	54.17%	22	45.83%	183	96.83%	6	3.17%	209	88.19%	28	11.81%
0.80	22	45.83%	26	54.17%	186	98.41%	3	1.59%	208	87.76%	29	12.24%
0.90	7	14.58%	41	85.42%	189	100.00%	0	0.00%	196	82.70%	41	17.30%
1.00	0	0.00%	48	100.00%	189	100.00%	0	0.00%	189	79.75%	48	20.25%

[a/] The Sample is divided into two subsample : 60% of the whole sample as the in-sample and 40% of the whole sample as the out-sample.
[b/] Bankruptcy prediction accuracy is code as (1,1) or a bankrupt firm(1) is correctly classified.
[c/] Type I Error is coded as (1,0) or a bankrupt firm (1) is misclassified as a nonbankrupt firm (0).
[d/] Nonbankruptcy predicton accuracy is coded as (0,0) or a nonbankrupt firm (0) is correctly classified.
[e/] Type II Error is coded as (0,1) or a nonbankrupt firm (0) is misclassified as a bankrupt firm (0).

Table 4: The Default Probability from the Logit Model

Panel C: Out-sample [a/]

Cutoff Point	Bankruptcy Prediction				Nonbankruptcy Prediction				Total Prediction			
	Accuracy [b/]		Type I Error [c/]		Accuracy [d/]		Type II Error [e/]		Accuracy		Error	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
0.10	28	87.50%	4	12.50%	88	70.40%	37	29.60%	116	73.89%	41	26.11%
0.20	25	78.13%	7	21.88%	98	78.40%	27	21.60%	123	78.34%	34	21.66%
0.30	23	71.88%	9	28.13%	102	81.60%	23	18.40%	125	79.62%	32	20.38%
0.40	22	68.75%	10	31.25%	107	85.60%	18	14.40%	129	82.17%	28	17.83%
0.50	21	65.63%	11	34.38%	108	86.40%	17	13.60%	129	82.17%	28	17.83%
0.60	19	59.38%	13	40.63%	112	89.60%	13	10.40%	131	83.44%	26	16.56%
0.70	17	53.13%	15	46.88%	114	91.20%	11	8.80%	131	83.44%	26	16.56%
0.80	11	34.38%	21	65.63%	119	95.20%	6	4.80%	130	82.80%	27	17.20%
0.90	9	28.13%	23	71.88%	123	98.40%	2	1.60%	132	84.08%	25	15.92%
1.00	2	6.25%	30	93.75%	125	100.00%	0	0.00%	127	80.89%	30	19.11%

[a/] The Sample is divided into two subsample : 60% of the whole sample as the in-sample and 40% of the whole sample as the out-sample.
[b/] Bankruptcy prediction accuracy is code as (1,1) or a bankrupt firm(1) is correctly classified.
[c/] Type I Error is coded as (1,0) or a bankrupt firm (1) is misclassified as a nonbankrupt firm (0).
[d/] Nonbankruptcy predicton accuracy is coded as (0,0) or a nonbankrupt firm (0) is correctly classified.
[e/] Type II Error is coded as (0,1) or a nonbankrupt firm (0) is misclassified as a bankrupt firm (0).

Table 5: The Prediction of the KMV model

Cutoff Point	Bankruptcy Prediction				Nonbankruptcy Prediction				Total Prediction			
	Accuracy [a/]		Type I Error [b/]		Accuracy [c/]		Type II Error [d/]		Accuracy		Error	
	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
0.10	43	58.11%	31	41.89%	230	74.19%	80	25.81%	273	71.09%	111	28.91%
0.20	25	33.78%	49	66.22%	289	93.23%	21	6.77%	314	81.77%	70	18.23%
0.30	20	27.03%	54	72.97%	301	97.10%	9	2.90%	321	83.59%	63	16.41%
0.40	15	20.27%	59	79.73%	306	98.71%	4	1.29%	321	83.59%	63	16.41%
0.50	10	13.51%	64	86.49%	309	99.68%	1	0.32%	319	83.07%	65	16.93%
0.60	5	6.76%	69	93.24%	310	100.00%	0	0.00%	315	82.03%	69	17.97%
0.70	3	4.05%	71	95.95%	310	100.00%	0	0.00%	313	81.51%	71	18.49%
0.80	0	0.00%	74	100.00%	310	100.00%	0	0.00%	310	80.73%	74	19.27%
0.90	0	0.00%	74	100.00%	310	100.00%	0	0.00%	310	80.73%	74	19.27%
1.00	0	0.00%	74	100.00%	310	100.00%	0	0.00%	310	80.73%	74	19.27%

[a/] Bankruptcy prediction accuracy is code as (1,1) or a bankrupt firm(1) is correctly classified.

[b/] Type I Error is coded as (1,0) or a bankrupt firm (1) is misclassified as a nonbankrupt firm (0).

[c/] Nonbankruptcy predicton accuracy is coded as (0,0) or a nonbankrupt firm (0) is correctly classified.

[d/] Type II Error is coded as (0,1) or a nonbankrupt firm (0) is misclassified as a bankrupt firm (0).

Table 6: KMV and Logit Model Relationship Test

Dependent Variable (EDF)	Coefficient of independent Variable		Adjusted R^2
	Constant	LOGIT	
1992	0.0088	0.3117*	0.2392
	(0.18)	(3.77)	
1993	0.0297*	0.0481*	0.1551
	(3.84)	(3.28)	
1994	0.0154	0.0246	0.0176
	(1.73)	(1.45)	
1995	0.0099	0.0845**	0.0482
	(0.49)	(2.14)	
1996	0.0090	0.0838**	0.0567
	(0.55)	(2.47)	
1997	0.0116	0.2647*	0.2023
	(0.42)	(4.91)	
1992-1997	0.0128	0.1412*	0.1124
	(1.27)	(7.26)	

Remarks: *,** significant at 1%, 5% level, ( ) t-statistical value

Table 7: Regression of Market Model and Default Probabilities

$$E(R_{it}) = \alpha + \beta_k R_{mt} + \beta_j EDF_{it}$$

Where R_{it} = the stock returns of each listed company i , at any time t
R_{mt} = the SET index returns at any time t
EDF_{it} = the default probability of each listed company i, at any time t

Panel A: Whole Period (1992-1999)

	Estimate of Coefficient	Adjusted R^2
Constant	-0.1748*	
	(-5.880)	
SET	1.5096*	0.4295
	(73.26)	
EDF	0.4860*	
	(4.16)	

Panel B: Prior Crisis (1992-1996)

	Estimate of Coefficient	Adjusted R^2
Constant	-0.1230*	
	(-5.39)	
SET	1.3521*	0.4444
	(60.93)	
EDF	0.4221**	
	(2.40)	

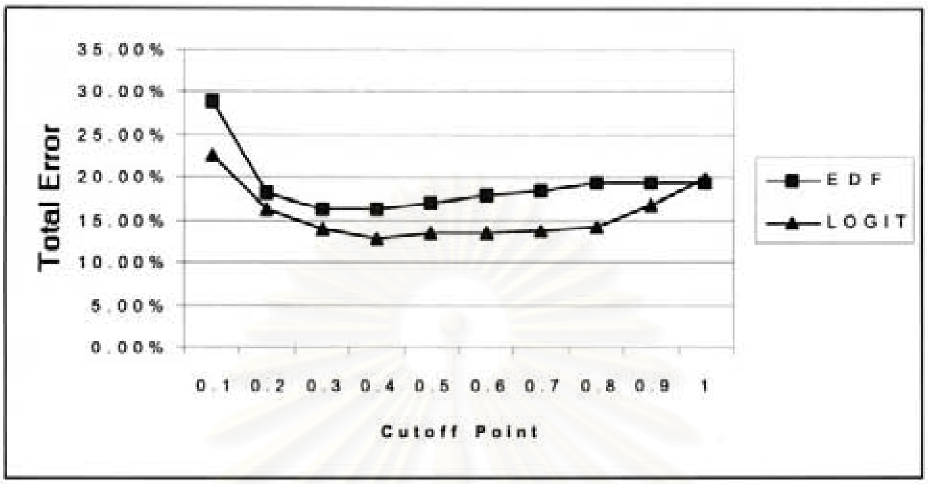
Panel C: Post-Crisis (1998-1999)

	Estimate of Coefficient	Adjusted R^2
Constant	-0.1989	
	(-1.76)	
SET	1.5513*	0.4607
	(35.49)	
EDF	0.9923*	
	(4.02)	

Remarks: *, ** significant at 1%, 5% level, ( ) t-statistical value

Figure 1: The Prediction Error at each Cut off Point

A: Total Prediction Error



B: Type I Error

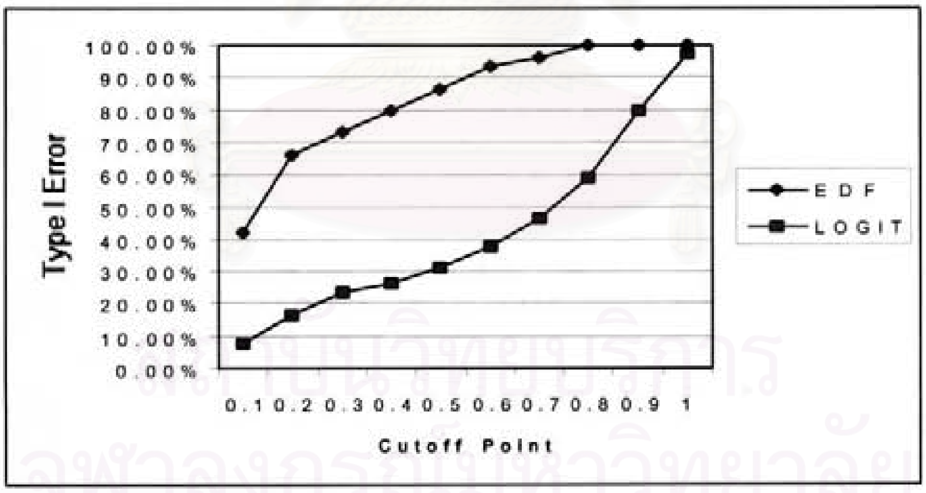


Figure 1: The Prediction Error at each Cut off Point

C: Type II Error

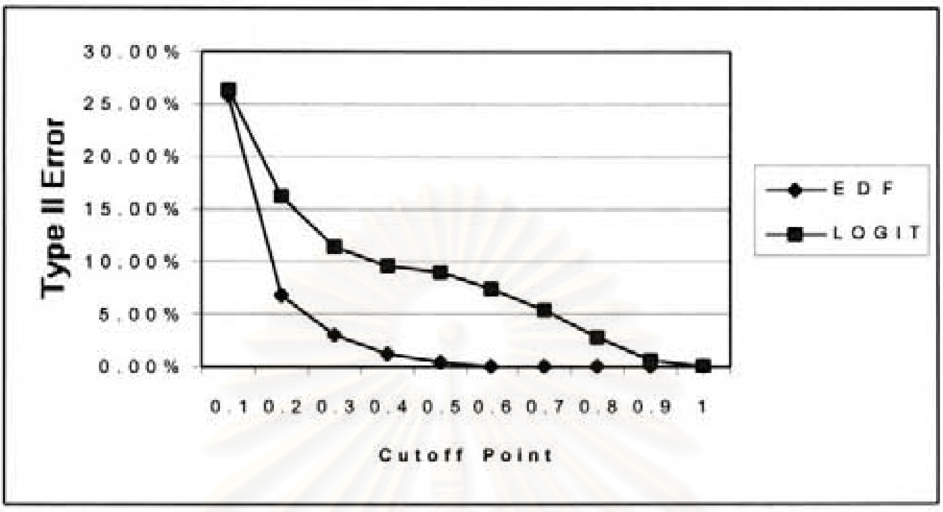


Figure 2: Average Sector Default Probability during 1992-1999 using KMV Model

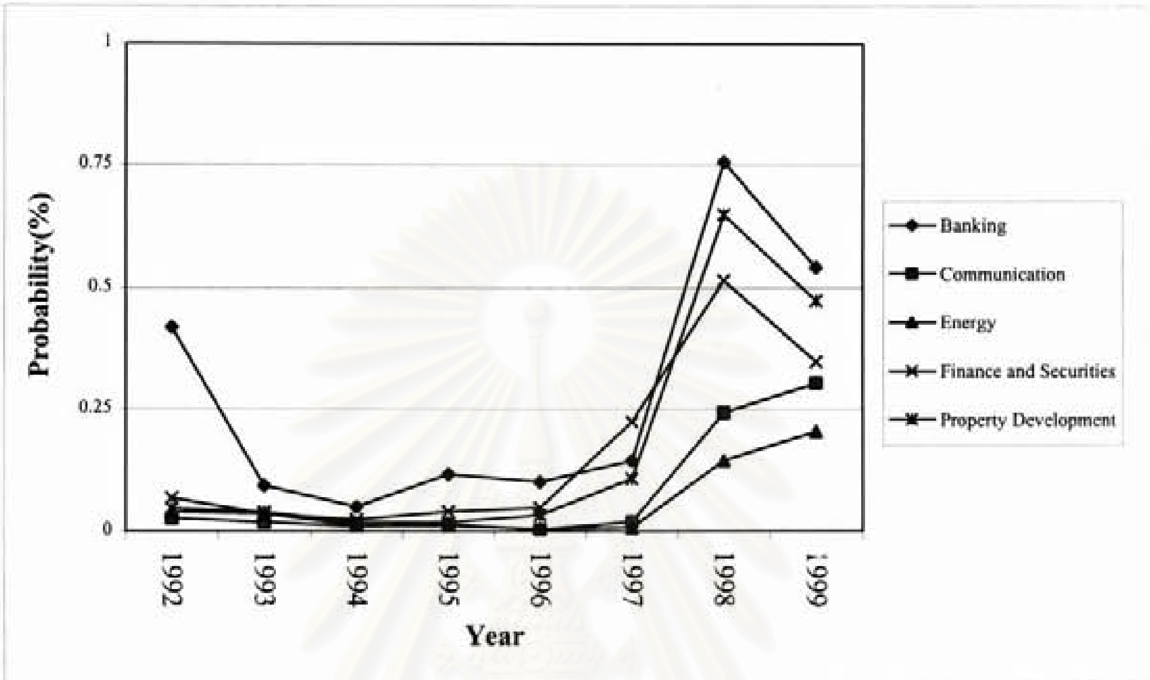
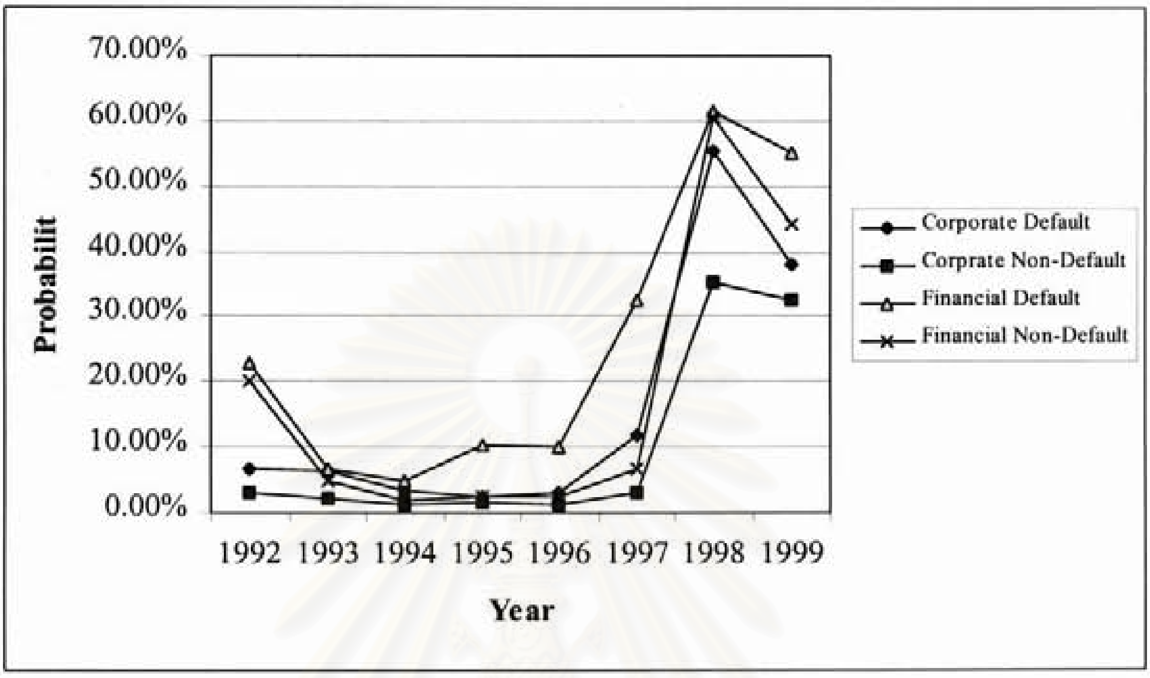


Figure 3: Average Default Probability during 1992-1999 using KMV Model



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Appendix 1: List of Top 100 Thai Listed Companies using in KMV Model

Code	Name
AA	ADVANCE AGRO PUBLIC COMPANY LIMITED
ADVANC	ADVANCED INFO SERVICE PUBLIC COMPANY LIMITED
AMARIN	AMARIN PLAZA PUBLIC COMPANY LIMITED
ASL	ADKINSON SECURITIES PUBLIC COMPANY LIMITED
AST	ABN AMRO ASIA SECURITIES PUBLIC COMPANY LIMITED
ATEC	ALPHATEC ELECTRONICS PUBLIC COMPANY LIMITED
BANPU	BANPU PUBLIC COMPANY LIMITED
BAY	BANK OF AYUDHYA PUBLIC COMPANY LIMITED
BBC	THE BANGKOK BANK OF COMMERCE PUBLIC COMPANY LIMITED
BBL	BANGKOK BANK PUBLIC COMPANY LIMITED
BCHANG	BAN CHANG GROUP PUBLIC COMPANY LIMITED
BCP	THE BANGCHAK PETROLEUM PUBLIC COMPANY LIMITED
BECL	BANGKOK EXPRESSWAY PUBLIC COMPANY LIMITED
B-LAND	BANGKOK LAND PUBLIC COMPANY LIMITED
BMB	BANGKOK METROPOLITAN BANK PUBLIC COMPANY LIMITED
BOA	THE BANK OF ASIA PUBLIC COMPANY LIMITED
CK	CH.KARNCHANG PUBLIC COMPANY LIMITED
CMIC	CMIC FINANCE AND SECURITIES PUBLIC COMPANY LIMITED
CNS	CAPITAL NOMURA SECURITIES PUBLIC COMPANY LIMITED
CNTRY	COUNTRY (THAILAND) PUBLIC COMPANY LIMITED
CPH	CASTLE PEAK HOLDINGS PUBLIC COMPANY LIMITED
DEFT	DYNAMIC EASTERN FINANCE THAILAND (1991) PUBLIC CO.,LTD.
DS	DHANA SIAM FINANCE PUBLIC COMPANY LIMITED
DTDB	DBS THAI DANU BANK PUBLIC COMPANY LIMITED
EFS	EKACHART FINANCE PUBLIC COMPANY LIMITED

Appendix 1(Cont.): List of Top 100 Thai Listed Companies using in KMV Model

Code	Name
EGCOMP	ELECTRICITY GENERATING PUBLIC COMPANY LIMITED
FBCB	FIRST BANGKOK CITY BANK PUBLIC COMPANY LIMITED
FCI	FIRST CITY INVESTMENT PUBLIC COMPANY LIMITED
FIN1	FINANCE ONE PUBLIC COMPANY LIMITED
GF	GENERAL FINANCE & SECURITIES PUBLIC COMPANY LIMITED
HEMRAJ	HEMARAJ LAND AND DEVELOPMENT PUBLIC COMPANY LIMITED
IEC	THE INTERNATIONAL ENGINEERING PUBLIC COMPANY LIMITED
IFCT	THE INDUSTRIAL FINANCE CORPORATION OF THAILAND
ITD	ITALIAN-THAI DEVELOPMENT PUBLIC COMPANY LIMITED
ITF	ITF FINANCE AND SECURITIES PUBLIC COMPANY LIMITED
JASMIN	JASMINE INTERNATIONAL PUBLIC COMPANY LIMITED
JULDIS	JULDIS DEVELOP PUBLIC COMPANY LIMITED
KK	KIATNAKIN FINANCE PUBLIC COMPANY LIMITED
KMC	KRISDA MAHANAKORN PUBLIC COMPANY LIMITED
KTB	KRUNG THAI BANK PUBLIC COMPANY LIMITED
KTT	KRUNGTHAI THANAKIT PUBLIC COMPANY LIMITED
LANNA	LANNA LIGNITE PUBLIC COMPANY LIMITED
LH	LAND AND HOUSES PUBLIC COMPANY LIMITED
LOXLEY	LOXLEY PUBLIC COMPANY LIMITED
MDX	M.D.X. PUBLIC COMPANY LIMITED
NAVA	NAVA FINANCE PUBLIC COMPANY LIMITED
NEP	NEP REALTY AND INDUSTRY PUBLIC COMPANY LIMITED
NFS	NATIONAL FINANCE PUBLIC COMPANY LIMITED
NPAT	NITHIPAT FINANCE PUBLIC COMPANY LIMITED
NPC	NATIONAL PETROCHEMICAL PUBLIC COMPANY LIMITED

Appendix 1(Cont.): List of Top 100 Thai Listed Companies using in KMV Model

Code	Name
NTS	N.T.S. STEEL GROUP PUBLIC COMPANY LIMITED
ONE	ONE HOLDING PUBLIC COMPANY LIMITED
PDI	PADAENG INDUSTRY PUBLIC COMPANY LIMITED
PHATRA	PHATRA THANAKIT PUBLIC COMPANY LIMITED
PRIME	PRIME FINANCE & SECURITIES PUBLIC COMPANY LIMITED
PTTEP	PTT EXPLORATION AND PRODUCTION PUBLIC COMPANY
PYT	PRASIT PATANA PUBLIC COMPANY LIMITED
QH	QUALITY HOUSES PUBLIC COMPANY LIMITED
RR	RATTANA REAL ESTATE PUBLIC COMPANY LIMITED
SAFARI	SAFARI WORLD PUBLIC COMPANY LIMITED
SAMART	SAMART CORPORATION PUBLIC COMPANY LIMITED
SATTEL	SHIN SATELLITE PUBLIC COMPANY LIMITED
SCB	THE SIAM COMMERCIAL BANK PUBLIC COMPANY LIMITED
SCC	THE SIAM CEMENT PUBLIC COMPANY LIMITED
SCCC	SIAM CITY CEMENT PUBLIC COMPANY LIMITED
SCCF	SIAM CITY CREDIT FINANCE & SECURITIES PUBLIC COMPANY LIMITED
SDF	SRI DHANA FINANCE PUBLIC COMPANY LIMITED
SGACL	SG ASIA CREDIT PUBLIC COMPANY LIMITED
SGF	SIAM GENERAL FACTORING PUBLIC COMPANY LIMITED
SHIN	SHIN CORPORATIONS PUBLIC COMPANY LIMITED
SITCA	SITCA INVESTMENT & SECURITIES PUBLIC COMPANY LIMITED
SOMPR	SOMPRASONG LAND PUBLIC COMPANY LIMITED
S-ONE	KGI SECURITIES ONE PUBLIC COMPANY LIMITED
SPL	SIAM PANICH LEASING PUBLIC COMPANY LIMITED
SSI	SAHAVIRIYA STEEL INDUSTRIES PUBLIC COMPANY LIMITED

Appendix 1(Cont.): List of Top 100 Thai Listed Companies using in KMV Model

Code	Name
STAR	STAR BLOCK GROUP PUBLIC COMPANY LIMITED
SUC	SAHA-UNION PUBLIC COMPANY LIMITED
SUPALI	SUPALAI PUBLIC COMPANY LIMITED
SUSCO	SIAM UNITED SERVICES PUBLIC COMPANY LIMITED
TA	TELECOMASIA CORPORATION PUBLIC COMPANY LIMITED
TATL	TECHNOLOGY APPLICATIONS (THAILAND) PUBLIC COMPANY LIMITED
TC	TROPICAL CANNING (THAILAND) PUBLIC COMPANY LIMITED
TFB	THE THAI FARMERS BANK PUBLIC COMPANY LIMITED
TFS	THAI FINANCIAL SYNDICATE PUBLIC COMPANY LIMITED
THAI	THAI AIRWAYS INTERNATIONAL PUBLIC COMPANY LIMITED
TMB	THE THAI MILITARY BANK PUBLIC COMPANY LIMITED
TPI	THAI PETROCHEMICAL INDUSTRY PUBLIC COMPANY LIMITED
TPIPL	TPI POLENE PUBLIC COMPANY LIMITED
TT&T	THAI TELEPHONE & TELECOMMUNICATION PUBLIC COMPANY LIMITED
TTF	THAI TANAKORN FINANCE PUBLIC COMPANY LIMITED
TYONG	TANAYONG PUBLIC COMPANY LIMITED
UAF	UNION ASIA FINANCE PUBLIC COMPANY LIMITED
UBC	UNITED BROADCASTING CORPORATION PUBLIC CO., LTD.
UCOM	UNITED COMMUNICATION INDUSTRY PUBLIC COMPANY LIMITED
UCT	UNICORD PUBLIC COMPANY LIMITED
UNITED	UNITED FINANCE CORPORATION PUBLIC COMPANY LIMITED
UNIVES	UNIVEST LAND PUBLIC COMPANY LIMITED
VNT	VINYTHAI PUBLIC COMPANY LIMITED
WALL	WALL STREET FINANCE AND SECURITIES PUBLIC COMPANY LIMITED
WAT	WATTACHAK PUBLIC COMPANY LIMITED