

การเปลี่ยนแปลงของอันดับความน่าเชื่อถือและความน่าจะเป็นในการผิดนัดชำระหนี้ของบริษัท



นาย วิทยา ปิยะอารยะนันท์

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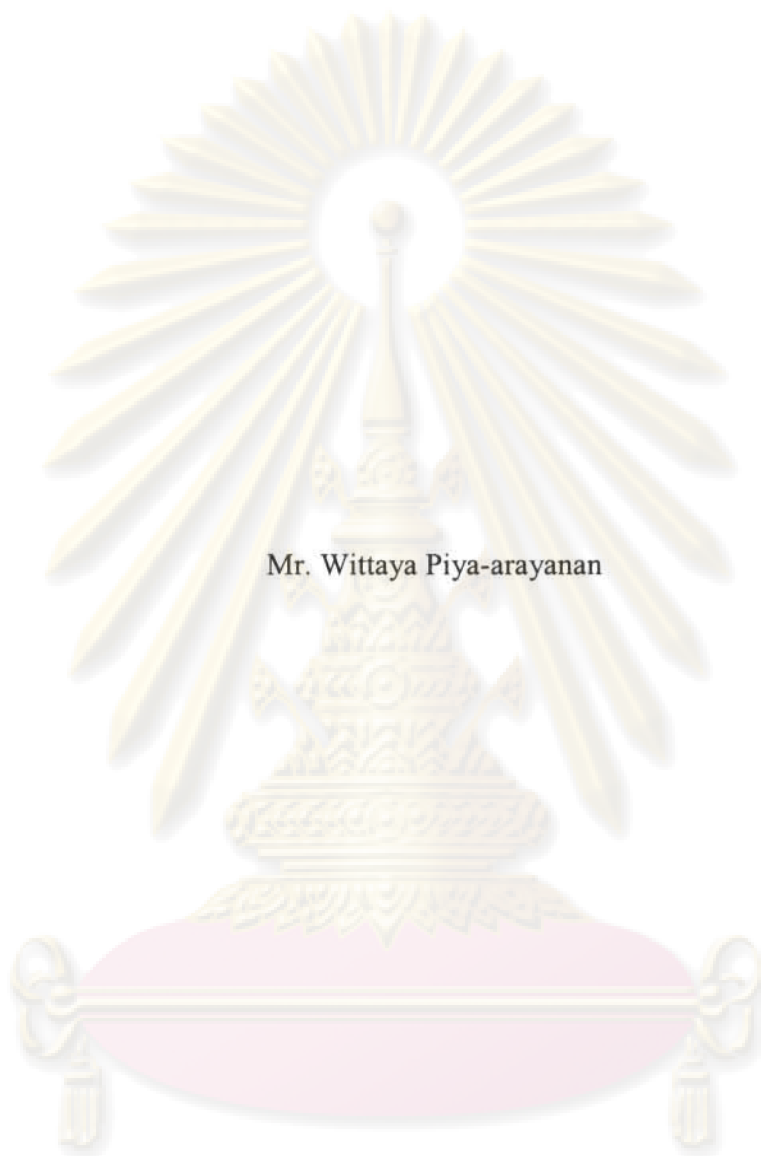
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CREDIT RATING CHANGE AND CHANGE IN FIRM'S
PROBABILITIES OF DEFAULT



Mr. Wittaya Piya-arayanan

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Finance

Department of Banking and Finance

Faculty of Commerce and Accountancy

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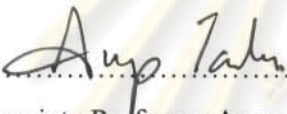
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By Mr. Wittaya Piya-arayanan


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Thesis Principal Advisor Associate Professor Sunti Tirapat, Ph.D.


Accepted by the Faculty of Commerce and Accountancy, Chulalongkorn
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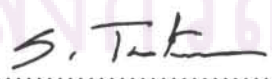
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THESIS COMMITTEE

.....Chairperson
(Assistant Professor Seksan Kiatsupaibul, Ph.D.)

* .....Thesis Principal Advisor
(Associate Professor Sunti Tirapat, Ph.D.)

.....External Member
(Sanphet Sukhapesna, Ph.D.)

.....Member
(Suparatana Tanthanongsakkun, Ph.D.)

วิทยา ปิยะอารยะนันท์: การเปลี่ยนแปลงของอันดับความน่าเชื่อถือและความน่าจะเป็นในการผิดนัดชำระหนี้ของบริษัท. (CREDIT RATING CHANGE AND CHANGE IN FIRM'S PROBABILITIES OF DEFAULT) อ. ที่ปรึกษาวิทยานิพนธ์หลัก: รศ.ดร. สันติ ธิรพัฒน์, 67 หน้า.

วิทยานิพนธ์ฉบับนี้ ทำการศึกษาเชิงประจักษ์เรื่องการเปลี่ยนแปลงของอันดับความน่าเชื่อถือและความน่าจะเป็นในการผิดนัดชำระหนี้ของบริษัท ตัวแทนจัดอันดับความน่าเชื่อถือจะจัดอันดับความน่าเชื่อถือของบริษัทจากข้อมูลในอดีตของบริษัท ในขณะที่ความน่าจะเป็นในการผิดนัดชำระหนี้ที่คำนวณได้จากแบบจำลองของเมอร์ตันเป็นการวัดความน่าจะเป็นที่บริษัทจะผิดนัดชำระหนี้ในอนาคต ดังนั้นการเปลี่ยนแปลงของอันดับความน่าจะเป็นในการผิดนัดชำระหนี้จึงน่าที่จะพยากรณ์การเปลี่ยนแปลงของอันดับความน่าเชื่อถือในอนาคตได้ ผลการศึกษาพบว่า ความน่าจะเป็นในการผิดนัดชำระหนี้ของบริษัทจะเปลี่ยนแปลงอย่างมีนัยสำคัญก่อนหน้าทีอันดับความน่าเชื่อถือของบริษัทจะเปลี่ยนแปลง นอกจากนี้ยังพบว่าหลังการเปลี่ยนแปลงของอันดับความน่าเชื่อถือ ความน่าจะเป็นในการผิดนัดชำระหนี้ของบริษัทเปลี่ยนแปลงที่ระดับนัยสำคัญต่างกัน ระหว่างการลดลงและเพิ่มขึ้นของอันดับความน่าเชื่อถือ และผลของการศึกษายังพบว่าความสัมพันธ์ของความน่าจะเป็นในการผิดนัดชำระหนี้และอันดับความน่าเชื่อถือของบริษัทจะแปรผกผันซึ่งกันและกันอย่างมีนัยสำคัญ และผลของการศึกษายังพบอีกว่าการเพิ่มความน่าจะเป็นในการผิดนัดชำระหนี้ เป็นตัวแปรในการพยากรณ์การเพิ่มขึ้น หรือลดลงของอันดับความน่าเชื่อถือของบริษัท สามารถเพิ่มความสามารภในการพยากรณ์ได้ จึงสรุปได้ว่าการเปลี่ยนแปลงของอันดับความน่าจะเป็นในการผิดนัดชำระหนี้สามารถใช้ในการพยากรณ์การเปลี่ยนแปลงของอันดับความน่าเชื่อถือของบริษัทได้

ศูนย์วิทยทรัพยากร

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WITTAYA PIYA-ARAYANAN: CREDIT RATING CHANGE AND CHANGE IN FIRM'S PROBABILITIES OF DEFAULT. THESIS PRINCIPAL ADVISOR: ASSOC. PROF. SUNTI TIRAPAT, Ph.D., 67 pp.

This thesis provides new empirical evidence on the credit risk literature. Rating agencies regularly measure the probabilities of default on current and historical data, they are not forward looking. Merton models, on the other hand, can provide forward-looking risk neutral probabilities of default. Changes in these risk neutral probabilities of default might provide leading information about changes in credit quality of debt issuer, and thus about either credit rating changes or default. This thesis attempts to bridge this gap. There are three main results are found in this study. First, risk neutral probabilities of default changed significantly before credit rating changes event. Moreover, after credit rating changes event, there is asymmetry of statistically significant changes in risk neutral probabilities of default between credit rating downgrades and credit rating upgrades, as same as study of impact of credit rating changes on stock and bond return. Second, the relationship between risk neutral probabilities of default and credit rating categories is significantly negative relation as expected. Finally, including risk neutral probabilities of default into rating changes prediction model can improve predictive power of the model. Therefore, changes in risk neutral probabilities of default can be used to predict for credit rating changes in the future.

Department: Banking and Finance Student's Signature:.....*Wittaya Piya-Arayanan*.....
 Field of Study: Finance Principal Advisor's Signature:.....*Sunti Tirapat*.....
 Academic Year: 2007

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CHAPTER I

Introduction

1.1 Background and Problem Review

The main role of the credit rating agencies is to convey opinions to financial markets about the creditworthiness of debt instruments and issuers. Credit rating agencies reduce lender's information gathering and facilitate the operation of securities market. In the core of Basel II, credit rating agencies will also play an even more central role than they have so far. However, the performance of rating agencies has been widely debated for inaccurate rating and slow reaction to new information, including Enron and WorldCom which carried investment grade ratings just a few months before their collapse. Nevertheless, some studies of credit rating changes show that the stock market reacts negatively to rating downgrade announcement at and after the announcement date. They, on the other hand, found no significantly stock price reaction to the announcement of credit rating upgrades. These evidence shows that somehow credit rating announcement still have the effect on firm's stock return. So, many literatures try to model the credit rating prediction and credit rating changes prediction based on available market information.

Rating agencies regularly measure the probabilities of default on current and historical data, they are not forward looking. Merton models, on the other hand, can provide forward-looking risk neutral probabilities of default. Changes in these risk neutral probabilities of default might provide leading information about changes in credit quality of debt issuer, and thus about either credit rating changes or default. For the purpose of investigating and comparing credit rating and risk neutral probabilities of default, levels of risk neutral probabilities of default by rating category are first

thing to check. If levels of risk neutral probabilities of default are higher for riskier rating grades, then risk neutral probabilities of default has done a good job as proxy for credit quality of debt issuer.

Previous rating prediction models (e.g. Horrigan (1966), West (1970), and Pinches and Mongo (1973)) and rating changes prediction models (e.g. Bhandari, Soldofsky, and Boe (1983)) base mostly on the firm's characteristic publish information on key financial ratio as their variables. These characteristics contain the measurement of leverage, interest coverage, profitability and risk. In this study, credit rating changes will be examined by another credit risk measurement, which are risk neutral probabilities of default by Merton's model. Credit risks measured by Merton's model reflect the information from the market through stock price. Furthermore, recent Moody's KMV research paper (Navneet, Jeffrey, and Zhu (2005)) indicate that Merton's model have the ability to predict spreads in the credit default swap (CDS) market. We expected the same benefit from the Merton's model with the rating prediction and rating changes prediction. Though the goal of this paper is to predict rating changes by changes in risk neutral probabilities of default, changes in risk neutral probabilities of default around credit rating changes are also investigated. We must know how risk neutral probabilities of default changes around the rating revision period so we can model for the rating changes prediction. Moreover, previous literatures that study the impact of credit rating changes on stock and bond returns found asymmetry market response to rating upgrades and downgrades. Study the changes in risk neutral probabilities of default around credit rating changes may be support this evidence if the same asymmetry market reaction was found.

1.2 Statement of Problem / Research Questions

To bridge the gap that discussed above, the problem to be investigated in this thesis can be stated as follows:

How risk neutral probabilities of default changes around the rating revision period? And;

Are risk neutral probabilities of default a useful predictor for credit rating changes?

1.3 Objective of the Study

To investigate the changes of risk neutral probabilities of default around rating revision period and examine the usefulness of risk neutral probabilities of default as credit rating change prediction.

1.4 Scope of the Study

The sample consists of all the listed firms rated by Standard and Poor's in S&P500 index year 2006. The monthly data range is 10 years, from 1997 to 2006. There are 431 firms rated by Standard and Poor's in S&P500 index between 1997 and 2006 while 327 firms face credit upgrade and downgrade during that time. The firm's credit ratings are collected from Reuter's database while the accounting data of listed firms in S&P500 is obtained from DATASTREAM.

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1.5 Contribution

This thesis seeks to provide empirical evidence on one of the most important gaps in the credit risk literature; no prior studies directly model the rating changes prediction by using the risk neutral probabilities of default from Merton's model as the independent variable. This paper also provides better understanding about the relationship between credit rating changes and risk neutral probabilities of default. Additionally, the by-product benefit of this thesis is to provide evidence on the asymmetry market response to credit rating upgrade and downgrade by looking at changes in risk neutral probabilities of default around credit rating revision.

1.6 Organization of the Study

The remaining of this paper is organized as following. Chapter 2 discusses the literature reviews, the theoretical background of the study. It reviews how the credit rating changes influence stock and bond returns, previous credit rating prediction and credit rating changes prediction; also, relationship between credit rating changes and probabilities of default are discussed. Chapter 3 describes data and methodology. It discusses the data collection, the research hypotheses, and Merton's model, ordered probit model and binary probit model backgrounds. Chapter 4 provides the results of descriptive statistic along with event studies, ordered probit analysis and binary probit analysis. Finally, conclusion and recommendations are provided in the Chapter 5.

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CHAPTER II

Literature Review

Credit risk has been one of the most active areas of recent financial research. Many papers tried to measure credit risk in several ways. One of them is measured by firm's probabilities of default from the option-based Black-Scholes model. Another important research area analyzes the meaning, role, and influence of credit ratings (see, Richard Cantor, 2004). There are many literatures indicating the impact of credit rating changes on stock and bond returns, as same as the rating prediction and rating changes prediction models. However, a few papers provide the evidence for relationship between credit rating changes and firm's probabilities of default. This section is described as follows; Section 2.1 reviews the several methods for credit risk measurement. Section 2.2 describes impact of credit rating changes on stock and bond returns, the rating prediction and rating changes prediction model are presented in section 2.3, and the relationships between credit rating and probabilities of default are described in section 2.4.

2.1 Credit Risk Measurements

Credit risk or default risk has been measured in a variety of ways. Merton (1974) was the first who modeled the firm's credit risk with the Black and Scholes (1973) methodology. Recognized that firm's stock is equivalent to a long position in a call option on the firm's assets, Merton used this correspondence to derive the market value and volatility of the firm's assets and then applied Black-Scholes option pricing model to calculate for the firm's probabilities of default.

The basic Merton's model has been extended in many ways. Geske (1977, 1979) extended Merton's model for compound options. Since firms, in general, have

both short-term debt and long-term debt, Geske's model can provide the "Short" probabilities of default for the short-term debt, the "Forward" probabilities of default for the long-term debt, conditional on not defaulting on the short-term debt, and "Total" probabilities of default on both short-term or long-term debt. Moody's KMV developed Expected Default Frequency (EDF) measurement; applied actual default rate and calculated default point to Merton's model provide more accurate and timelier assessment of credit and default risk. Turnbull (1979) includes corporate taxes and bankruptcy costs into Merton's model. Kim, Ramaswamy, and Sunderasan (1989) studied the interaction of credit risk and interest rate risk by allowing the risk-free rate to follow a square root process. They showed that credit risk is not sensitive to the interest rate volatility but is sensitive to interest rate expectations.

Altman et al. (1977) used a credit scoring approach which is z-scores and discriminant analysis to measure risky corporate debt. Another approach assumes default as a rare event, or Poisson distribution process. Changing expectations concerning the likelihood of default are captured by the stochastic properties of the hazard rate process h . the conditional probabilities of default at time t over the next instant of time length Δt is approximately $h_t \Delta t$. Shumway (2001) argue that hazard models which produce consistent estimates are more appropriate than single period models for forecasting bankruptcy because it corrects for period at risk and allows for time-varying covariates. Duffie and Singleton (1997) price interest rate swap contract by modeling the default time as an inaccessible stopping time, such as a Poisson arrival. Jarrow and Turnbull (1995) model default as a Poisson event when pricing derivatives subjected to credit risk.

2.2 Impact of credit rating changes on stock and bond returns

Holthausen and Leftwich (1986) studied the effect of bond rating changes on common stock prices in US financial market. The evidence suggests that only downgrade announcements are associated with negative abnormal stock returns. But bond upgrades found no stock price response to announcement. They also indicate two potential explanations on the market response differently to rating upgrades and downgrades. Firstly, firms are more likely to convey the good news to the market than bad news. Market already absorbs the good news before credit rating agencies announce rating upgrades. Secondly, rating agencies may have asymmetric loss functions; upgrades are not timely as downgrades.

Hand, Holthausen, and Leftwich (1992) examine both daily excess bond and stock returns associated with announcements of additions to Credit Watch List, and to rating changes. They found that excess bond returns for additions to the Credit Watch List are insignificant until the expected rating changes are excluded. In addition, statistically significant average excess bond and stock returns to rating downgrades are observed, with less reliable effects for upgrades. Asymmetric results with respect to rating downgrades and upgrades were found. They observe significantly negative excess bond and stock returns for rating downgrades, but weaker positive excess bond and stock returns for upgrades. However, the asymmetries in excess bond returns disappear when non-contaminated samples are examined. Despite the inconsistencies, they concluded that there are both bond and stock price effects associated with both announcements of additions to Credit Watch List and announcements of actual rating changes by rating agencies.

Ederington and Goh (1998) explored the relative information provided to equity market by rating agencies and stock analysts. They conduct an event study of

the stock price reaction to rating changes. The results indicated significant negative stock market reaction to downgrade announcements but no reaction to upgrade announcements. Moreover, they found significantly abnormal return prior to both upgrade and downgrade announcements. They concluded either that rating agencies expend more resources in detecting deteriorations in a firm's financial position that they do in detecting improvements or that the firms themselves communicate good news, but not bad news, to the market.

Prior work that has used bond price data to examine the effect of rating changes has been mixed. Weinstein (1977) (monthly bond returns) did not find a price reaction at the time of rating changes. Ingram, Brooks and Copeland (1983) (monthly changes in municipal bond yields) and Hand, Holthausen, and Leftwich (1992) (daily data) found significant bond price reactions.

Other literatures relevant to the impact of credit rating changes on stock and bond returns are Barron, Clare, and Thomas (1997) and Choy, Gray, and Rangunathan (2006). They found the same evidence for stock returns (significant only for credit downgrade announcements) in UK and Australian stock market, respectively.

2.3 Rating prediction and rating changes prediction models

Various studies that tried to model bond ratings based on publicly available financial information showed fairly good results. Horrigan (1966) presented the study to estimate and predict bond ratings based on both issuing firms and bonds characteristics. 200 bonds with unchanged ratings was studied in 1959-64 to make a model to predict both new issuing bond and changes in bond ratings in 1961-64 period. He focused on firm's financial data and ratios from the most recent accounting period as independent variables. He regress the ratings corporate bond issues with

many different independent variables and then selected the ratios which are the highest correlation with the ratings (or the highest R^2 in regression equations). The independent variables Horrigan finally choose were: total assets, working capital over sale, net worth over total debt, sales over net worth, and net operating profit over sale. Moreover, he also found that the subordination status (using 0-1 dummy variable) was important in explaining the variability of bond ratings. The subordination status and total assets variables were the two most significant variables in the regression. The explanation power of the six independent variables is 65%. His predictions were correct for 55% of both newly rating and rating changed by Moody's during the period 1961-64.

West (1970) argued with Fisher (1959) that risk premium is highly correlated with ratings, so the same variables should also perform well as predictors of ratings. The four variables in Fisher's study used in West model all in logarithmic form were: earnings variability (coefficient of variation for previous 9 years earnings), period of solvency (number of year without loss to creditors), capital structure (debt equity ratio), and bonds outstanding (market value of firm's publicly traded bond). West obtained R^2 that ranges from .71 to .79 which are higher than those obtained by Horrigan, however, the predictive ability of West's model was about the same as Horigan's. West's model correctly predicted 62% of Moody's for the 1953 cross section and 60% for the 1961 cross section.

The interesting issue arises from Horrigan and West studies. Both studies used Ordinary Least-Squares (OLS) analysis which assumes that the dependent variable (rating categories) has been categorized into equally spaced discrete intervals. The result can implied that the risk differential between an Aaa and an Aa bond is the same as between a Ba and a B bond which, in fact, did not equal. In additional, when

the dependent variable of a regression is ordinal rather than interval, the expected value of the error term does not equal zero, the variance of the error term is not constant as a function of the independent variables, and the error term is not normally distributed. It is unclear what effect this misspecification has on Horrigan's and West's studies. Following studies on rating prediction used multiple discriminant analysis to classify bonds into rating categories. Pinches and Mingo (1973) used multiple discriminant analysis to develop the predictive model. An estimating sample of 132 bonds and a holdout sample of 48 bonds issued in 1967-68, with bond rating in the five Moody's categories from Aa to B, were chosen. The model variables are: subordination, years of consecutive dividend, size, net income over total assets, five year mean of net income plus interest over interest and long term debt over total assets. In their discriminant analysis, subordination was the most important variable. This model correctly predicted roughly 65% and 56% of the Moody's ratings for holdout samples in the periods 1967-68 and 1969.

Altman and Katz (1976) applied multiple discriminant analysis to the bond ratings of companies in the electric public utility industry. Starting from an initial list of 30 variables, variables which apparently contributed most to the discriminant function included the interest coverage ratio, earnings variability, interest coverage variability, return on investment, and maintenance and depreciation expense to operation revenues. The models correctly classify 80%-90% of the bonds in their estimation sample.

So far, a limited number of studies have investigated the issue whether rating changes can be predicted. Bhandari, Soldofsky and Boe (1983) analyze the bond rating changes by using both univariate statistical methods and discriminant analysis to find significant variables and their relationship with the changes. Their paper

presented The Bond Quality Rating Change model (BQRC) which is a discriminant function that incorporates both levels and trends of the three financial variables: times interest earned (TIE), debt ratio, and return on assets (ROA). The most important explanatory variable is return on assets, followed by the trend in the return on assets. They also concluded that most recent 5 years financial statement data carries information to predict an impending rating changes or no change for a company's credit rating.

2.4 Relationship between credit rating and probabilities of default

Kim and Nabar (2007) used bankruptcy prediction methodology (Shumway, 2001) and Chava and Jarrow (2004) model to examine the firm's probabilities of bankruptcy, and then analyze the changes in probabilities of bankruptcy around rating change announcements. The result from investigation indicates that firms whose bonds are upgraded significantly decrease in probabilities of bankruptcy prior to the rating changes but there is no change after the upgrade announcements. While downgraded firms significantly increase in their probabilities of bankruptcy both prior to and following the rating changes.

Delianedis and Geske (1998) compute risk neutral probabilities of default using the diffusion models of Merton (1974) and Geske (1977) and then perform the event study of the relationship between risk neutral probabilities of default and rating migration. They show that risk neutral probabilities of default from both models do possess significant and very early information about credit migrations. They also concluded that credit rating downgrades or default can be detected months in advance so these credit events may not be a surprise to the market.

Previous literature reviews show that many papers tried to predict rating and rating changes based on accounting information. However, credit risks measured by default probabilities also indicate some information prior to credit rating changes. To fulfill the gap, this paper will use credit risk measured by Merton's to model the rating changes prediction.



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CHAPTER III

Data and Methodology

3.1 Data

The samples include all rated firms by Standard and Poor's in S&P500 index year 2006. The data range is 10 years, from 1997 to 2006. Using the firms of the S&P500 Index in our sample has three main advantages. Firstly, the S&P500 Index consists of companies that are representative for a wide range of industries. Second, the vast majority of the S&P500 companies are rated by one or more rating agencies. A final advantage is that all S&P500 constituents are listed in the United States, which improves the comparability of the firms, as their shares are all denoted in the same currency.

Firm's credit ratings are collected from Reuter's database. There are 431 firms rated by Standard and Poor's in S&P500 index between 1997 and 2006 while 327 firms face credit upgrade and downgrade during that time (289 events for upgrade and 404 events for downgrade).

Since we want to examine changes in the firm's credit rating following changes in firm's risk neutral probabilities of default, a database of firm's trading and accounting information to calculate the risk neutral probabilities of default and to model the rating prediction and rating changes prediction is required. Moreover, risk neutral probabilities of default also require time to default and the risk-free rate. Time to default is assumed to be one year while 3 month US Treasury bill rate is used for risk-free rate. All above data are collected from DataStream database.

This paper uses six key accounting variables: market capitalization (stock price multiply by outstanding shares), beta (regress 3 years firm's monthly return against market return), debt/assets, long-term debt/assets, times interest earned

(operating income plus interest expenses divided by interest expenses) and return on asset, along with risk neutral probabilities of default as indicators of firm's credit rating and credit rating changes. All variables are limited between the 5th and 95th percentiles of their cross-sectional distributions to eliminate outliers.

3.2 Research Hypotheses

To conduct the objectives of this study, the following hypotheses will be empirically investigated.

Hypothesis 1: Risk neutral probabilities of default decrease (increase) before credit rating upgrade (downgrade) events.

Credit rating upgrades (downgrades) indicate lower (higher) firm's default risk. If risk neutral probabilities of default from Merton's model are forward-looking, the risk neutral probabilities of default should be significantly decrease before credit rating upgrades and increase before credit rating downgrades.

Hypothesis 2: Risk neutral probabilities of default significantly change after credit rating downgrade events but not for credit rating upgrade events.

Studies of impact of credit rating changes on stock returns indicate that downgrade announcements are associated with negative abnormal stock returns. But upgrades found no stock price response to announcement. Holthausen and Leftwich (1986) indicate potential explanations that market response differently to rating upgrades and downgrades. If Merton's model is able to extract the market information prior credit rating change event though stock price, the risk neutral probabilities of default should be significantly changed after credit rating downgrades announcement but not for upgrades.

Hypothesis 3: Changes in risk neutral probabilities of default are useful predictor for credit rating changes prediction.

Risk neutral probabilities of default from stock price are a forward looking or expected default frequencies while rating agencies compute credit rating from current and historical data. The changes in risk neutral probabilities of default may forecast the credit rating changes in the future.

3.3 Methodology

This thesis investigates the usefulness of risk neutral probabilities of default as credit rating change predictor. Firstly, we must calculate risk neutral probabilities of default for each firm in cross-sectional time-series framework. And then we will look through the analysis of market's reaction to rating change announcements. Next, we will apply the ordered probit model to rating prediction models to verify the usefulness of our variables. Finally, binary probit model is used for rating change prediction models.

3.3.1 Risk neutral probabilities of default

Equity holders have the residual claim on a firm's assets while being subject to limited liability. Merton (1974) recognized that equity in a firm is equivalent to a long position in a call option on the firm's assets, and used this correspondence to derive the market value and volatility of the firm's underlying assets. More precisely, Merton used Black and Scholes (1973) option pricing framework to solve for the asset value and volatility implied by the option price and the option volatility.

Merton (1974) model lies a modified version of the Black-Scholes formula linking the market value of equity and the market value of assets

$$V_E = V_A N(d_1) - e^{-rt} DN(d_2) \quad (1)$$

where; V_E Market value of the firm's equity
 V_A Market value of the firm's assets
 D Total amount of the firm's debt
 T Time to maturity of the firm's debt
 r Risk-free interest rate
 $N(.)$ univariate cumulative normal distribution function

$$d_1 \text{ equal to } \frac{\ln(V_A / D) + (r + \frac{1}{2} \sigma_A^2)T}{\sigma_A \sqrt{T}}$$

$$d_2 \text{ equal to } d_1 - \sigma_A \sqrt{T}$$

Moreover, it is easily shown that the equity and asset volatility are related by the expression

$$\sigma_E = \frac{V_A}{V_E} N(d_1) \sigma_A \quad (2)$$

where; σ_E and σ_A are volatilities of the firm's equity and asset returns respectively.

Solving the nonlinear system of equation (1) and (2) by iteration process gives V_A and σ_A , and the probabilities of default under risk neutral assumption (risk neutral probabilities of default) is calculate by $N(-d_2)$ or $1-N(d_2)$

3.3.2 Risk neutral probabilities of default changes around credit rating revision

Because one focus of this paper is to study the market's reaction to rating change announcements, event study methodology is used. To provide a check of the robustness of conclusions based on parametric tests, Non-parametric test is also included.

Parametric test

The test is based on risk neutral probabilities of default changes around the rating upgrades and downgrades announcements. The null hypothesis is that mean of the changes in rating revision firm's risk neutral probabilities of default are not different from the previous month risk neutral probabilities of default. Event window is seven months around the rating revision announcement (month -3 through month +3). T-test, which is used to indicate the significance levels, is calculated from the following equation;

$$T - test = \frac{\sum d}{\sqrt{\frac{n \sum d^2 - (\sum d)^2}{n-1}}} \quad (3)$$

where; d = difference between current month-end risk neutral probabilities of default and previous month-end risk neutral probabilities of default

n = number of sample

Non-parametric test – Wilcoxon signed-rank test

The Wilcoxon signed rank test is used to test the hypothesis that the population median of the paired differences of the two samples is 0. So, the null hypothesis is the median of the differences between current month-end risk neutral probabilities of default and previous month-end risk neutral probabilities of default is 0. Event window is seven months around the rating revision announcement (month -3 through month +3). Wilcoxon signed-rank test is calculated from the following equation;

$$Z = \frac{(W - \mu_w) \pm 0.5}{\sigma_w} \quad (4)$$

where; W = sum of the signed ranks

μ_w = mean of signed ranks which is in all instances equal to zero

σ_W = standard deviation of the sum of signed ranks distribution which is equal to $\sqrt{\frac{N(N+1)(2N+1)}{6}}$

3.3.3 Ordered Probit model

The empirical analysis for rating prediction in this paper applies an ordered probit model as same as Blumn, Lim, and Mackinlay (1998) paper. This model relates the rating categories to observed explanatory variables through an unobserved continuous linking variable. The rating categories map into a partition of the range of the unobserved variable, which is in turn a linear function of the observed explanatory variables.

In ordered dependent variable models, the observed y_i denotes outcomes representing ordered or ranked categories. We can model the observed response by considering a latent variable y_i^* that depends linearly on the explanatory variables x_i :

$$y_i^* = x_i\beta + \varepsilon_i \quad (5)$$

where; ε_i are independent and identically distributed random variables. The observed y_i is determined from y_i^* using the rule:

$$y_i = \begin{cases} 0 & \text{if } y_i^* < \mu_1 \\ 1 & \text{if } \mu_1 < y_i^* < \mu_2 \\ 2 & \text{if } \mu_2 < y_i^* < \mu_3 \\ \vdots & \vdots \\ M & \text{if } \mu_M < y_i^* \end{cases} \quad (6)$$

where; μ is a set of limit points that assign the range of latent variable y_i^* to the observed variable y_i .

Rating Prediction Model

The dependent variable is rating categories which are assigned the highest numerical value for the best credit rating (AAA) and then reduce to 1 for the worst rating category in this paper sample (CCC+). The firm characteristics used to estimate rating categories are based on Blumn, Lim, and MacKinlay (1998) paper and are defined as follow:

1. Firm size, measured as the natural logarithm of the market capitalization
2. Beta, estimated by a market model using two years of monthly returns
3. Debt ratio, measured by total debt over total assets
4. Long-term Debt ratio, measured by long-term debt over total assets
5. Times interest earned, measured by operating income plus interest expense divided by interest expense
6. Return on assets, measured by net income over total assets
7. Risk neutral probabilities of default, measured by Merton's model

So, the rating prediction model is end up with the following equation;

$$R_{it} = \beta_1 MktCap_{i,t-1} + \beta_2 BETA_{i,t-1} + \beta_3 DR_{i,t-1} + \beta_4 LTDR_{i,t-1} + \beta_5 TIE_{i,t-1} + \beta_6 ROA_{i,t-1} + \beta_7 RNPD_{i,t-1} + \varepsilon_i \quad (7)$$

where; R_{it} is rating categories of firm i at time t

$MktCap_{i,t-1}$ is Market capitalization of firm i at time $t-1$

$BETA_{i,t-1}$ is beta of firm i at time $t-1$

$DR_{i,t-1}$ is debt ratio of firm i at time $t-1$

$LTDR_{i,t-1}$ is long-term debt ratio of firm i at time $t-1$

$TIE_{i,t-1}$ is times interest earned of firm i at time $t-1$

$ROA_{i,t-1}$ is return on assets of firm i at time $t-1$

$RNPD_{i,t-1}$ is risk neutral probabilities of default of firm i at time $t-1$

Moreover, the ordered probit models also provide the expectation-prediction table for classify the observations on the basis of the predicted response. The ordered probit models perform the classification on the basis of maximum predicted probability as well as the expected probability

3.3.4 Binary Dependent Variable Models

The empirical analysis for rating change prediction in this paper applies the binary dependent variable models. In this class of models, y may take on only two values; y might be a dummy variable representing the occurrence of an event, or a choice between two alternatives.

Suppose that a binary dependent variable, y_i , takes on values of zero and one. A simple linear regression of y on x is not appropriate. The binary model is often motivated as a latent variables specification. Suppose that there is an unobserved latent variable y_i^* that is linearly related to x_i :

$$y_i^* = x_i\beta + u_i \quad (8)$$

where; u_i is a random disturbance. Then the observed dependent variable is determined by whether y_i^* exceeds a threshold value:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \quad (9)$$

Rating Change Prediction Model

Credit rating changes prediction for downgrades and upgrades has been separated. For credit rating downgrades prediction, the dependent variable is assigned the value of 1 if firm i at time t faced rating downgrade, 0 if other. For credit rating upgrades prediction, the dependent variable is assigned the value of 1 if firm i at time

t faced rating upgrade, 0 if other. The firm characteristics used to estimate rating changes categories are the same as the Bond Quality Rating Change (BQRC) model by Bhandari, Soldofsky and Boe (1983). The BQRC model included both level and trend measurement of three independent variables which are times interest earned ratio, times interest earned ratio trend, debt ratio, debt ratio trend, return on assets, return on asset trend. Residual standard error of the linear regression in return on assets trend measure is also included as the measure of earning stability. So, BQRC model end up with the following equation;

$$Z_{it} = \alpha + \beta_1 TIE_{i,t-1} + \beta_2 TIETrend_{i,t-1} + \beta_3 DR_{i,t-1} + \beta_4 DRTrend_{i,t-1} + \beta_5 ROA_{i,t-1} + \beta_6 ROATrend_{i,t-1} + \beta_7 ROARES_{i,t-1} + \varepsilon_i \quad (10)$$

where; Z_{it} is rating change categories of firm i at time t

(For upgrade prediction; upgrades = 1, other = 0)

(For downgrade prediction; downgrades = 1, other = 0)

$TIE_{i,t-1}$ is level of times interest earned ratio of firm i at time $t-1$

$TIETrend_{i,t-1}$ is slope of the regression of the five years times interest earned ratio data preceding the rating change (regressed against time)

$DR_{i,t-1}$ is level of debt ratio of firm i at time $t-1$

$DRTrend_{i,t-1}$ is slope of the regression of the five years debt ratio data preceding the rating change (regressed against time)

$ROA_{i,t-1}$ is level of return on assets of firm i at time $t-1$

$ROATrend_{i,t-1}$ is slope of the regression of the five years return on assets data preceding the rating change (regressed against time)

$ROARES_{i,t-1}$ is residual standard error of the linear regression in return on asset trend of firm i at time $t-1$

The above BQRC model is used as the reference model to compare with the other models that were added more independent variables. Another two independent variables which are market capitalization change and firm's beta change were added because a number of studies find a significant relation between credit ratings and level of firm's size and firm's equity risk (beta). The adjusted BQRC model for credit rating changes prediction is as follow;

$$\begin{aligned}
 Z_{it} = & \alpha + \beta_1 TIE_{i,t-1} + \beta_2 TIETrend_{i,t-1} + \beta_3 DR_{i,t-1} + \beta_4 DRTrend_{i,t-1} + \\
 & \beta_5 ROA_{i,t-1} + \beta_6 ROATrend_{i,t-1} + \beta_7 ROARES_{i,t-1} + \beta_8 \Delta MktCap_{i,t-1} + \\
 & \beta_9 \Delta Beta_{i,t-1} + \varepsilon_i
 \end{aligned} \tag{11}$$

where; $\Delta MktCap_{i,t-1}$ is difference between market capitalization of firm i at time $t-1$ from time $t-2$

$\Delta Beta_{i,t-1}$ is difference between beta of firm i at time $t-1$ from time $t-2$

Finally, changes in risk neutral probabilities of default are included in equation (11) and end up with the adjusted BQRC model with risk neutral probabilities of default equation;

$$\begin{aligned}
 Z_{it} = & \alpha + \beta_1 TIE_{i,t-1} + \beta_2 TIETrend_{i,t-1} + \beta_3 DR_{i,t-1} + \beta_4 DRTrend_{i,t-1} + \\
 & \beta_5 ROA_{i,t-1} + \beta_6 ROATrend_{i,t-1} + \beta_7 ROARES_{i,t-1} + \beta_8 \Delta MktCap_{i,t-1} + \\
 & \beta_9 \Delta Beta_{i,t-1} + \beta_{10} \Delta RNPD_{i,t-1} + \varepsilon_i
 \end{aligned} \tag{12}$$

where; $\Delta RNPD_{i,t-1}$ is difference between risk neutral probabilities of default of firm i at time $t-1$ from time $t-2$

For credit rating changes prediction, the out-of-sample test will be performed to evaluate the rating changes prediction model. The out-of-sample tests use prior five years data to predict for each firm's credit rating changes in recent year. For 10 years data, we will end up with 5 years out-of-sample test that give us more data to perform the test.

In addition, the accuracy of a test is evaluated using Receiver Operating Characteristic (ROC) curve analysis. In the ROC curve, the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points. Each point on the ROC plot represents a sensitivity/specificity pair corresponding to a particular decision threshold. A test with perfect discrimination (no overlap in the two distributions) has a ROC plot that passes through the upper left corner (100% sensitivity, 100% specificity). Therefore the closer the ROC plot is to the upper left corner, the higher the overall accuracy of the test. The example of the ROC curve is figure 1. Binary probit model is used to provide each sample value and then assign the cut-off point to separate the sample into downgrades or not downgrades (the value of one and zero). Vertical axis is the percentage of the “true” prediction for downgrade samples while horizontal axis is the percentage of the “false” prediction for not downgrades samples by the model. When we vary the cut-off point, we can make the ROC curve.

To measure the ROC curve, area under the ROC curve (AUC) will be used. z-statistic and p-value indicated whether the area under the ROC curve is significantly difference from 0.5. The models that can provide higher AUC is better than the models that have lower AUC. Statistical significance of the difference between the areas under 2 to 6 ROC curves is evaluated by comparison of the ROC curve test. z-statistic and p-value indicated whether the two compared areas are significantly different. The ROC curve used in this thesis is provided by MedCalc program (<http://www.medcalc.be/manual/roc.php>)

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CHAPTER IV

Results

The main objective of this study is to investigate the usefulness of risk neutral probabilities of default as a rating prediction and rating change prediction. However, firm characteristics are also included in the models because they proved to be useful prediction variables. This section starts with the descriptive statistics for the samples in this paper. And then begins the analysis by performing the event study for the changes in risk neutral probabilities of default around credit rating revisions in the second part. The rating prediction and rating change prediction will be presented in third and fourth part of this section.

4.1 Descriptive statistics

Table 1 shows the number of firm's rating in S&P500 index during the period from 1997 to 2006. The vast majority of firms in S&P500 index was rated investment grade (i.e. rating of BBB- or better) while the lowest rating is CCC+. Decreasing number of firms in superior rating (AAA and AA) from 1997 though 2006 indicated the tightening of rating agency standards after ENRON and WORLDCOM collapsed and the enhanced role proposed for ratings in bank regulation under Basel II (Amato and Furfine, 2004). The transition matrix of old and new rating for the sample is presented in the Table 2. There are 693 credit rating changes for the sample firms in S&P500 from 1997 though 2006 which can be divided into 404 downgrades and 289 upgrades.

Table 3 shows summary statistics of the variables that are used in rating prediction model. The variables are systematically related to rating categories. Bigger firms and those with small beta values receive better ratings while lower ratings are

assigned to firms with higher leverage, lower profitability, and lower times interest earned. Risk neutral probabilities of default show that credit rating agencies assign credit rating according to firm's probabilities of default. Firm's with low probabilities of default will be assigned high credit rating categories and vice versa.

Table 4 also shows summary statistics of the variables that are used in this paper for rating changes prediction model. The variables are systematically related to firm's rating changes status. Bigger firms and those with small beta values receive rating upgrades while rating downgrades are assigned to firms with positive leverage trend, negative profitability trend, and negative times interest earned trend. ROARES, a measure of earnings instability, is higher for firms whose credit ratings were downgraded than for firms whose credit ratings were upgraded. Changes in Risk neutral probabilities of default also indicate firm's rating changes status. Firm's with lower their probabilities of default will be assigned credit rating upgrades and vice versa. As expected, the group means of "no change" firms are between those of the two extreme groups.

4.2 Risk neutral probabilities of default changes around credit rating revision

Mean and median of changes in risk neutral probabilities of default around credit rating upgrades events and credit rating downgrades events are showed in figure 1 and figure 2, respectively. These two figures are showed mean and median of changes in risk neutral probabilities of default 24 months before and 12 months after credit rating revision events. For credit rating upgrades, mean and median of changes in risk neutral probabilities of default are negative before credit upgrades announcements. Credit rating downgrades firms, on the other hand, have positive changes in risk neutral probabilities of default before credit rating downgrades.

However, these two figures did not suggest any statistical evidence beside mean and median of the changes before rating revision are the same as we expected.

Table 5 presents statistics of risk neutral probabilities of default changes for a sample of 693 rating changes with 404 downgrades and 289 upgrades. Mean and median monthly changes in risk neutral probabilities of default are reported for a seven month test window around the rating revision (month₋₃ through month₊₃). Credit rating upgrades imply a reduced risk of financial distress; hence we expect upgrades to be associated with risk neutral probabilities of default decreases and vice versa for credit rating downgrades.

The results indicated that mean and median decrease in risk neutral probabilities of default in the three months period before the credit rating upgrades. Median of risk neutral probabilities of default change is significantly negative only in month₋₁. However, the mean and median risk neutral probabilities of default change are not statistically significant in the month of and after the credit upgrades. On the other hand, for firms whose credit rating is downgraded, risk neutral probabilities of default increase significantly both prior to and following the rating downgrades. These results are consistent with previous studies; Kim and Nabar (2007) use Chava and Jarrow (2004) model predict the bankruptcy probabilities. For firms whose credit ratings are downgraded, they found significantly increases in bankruptcy probabilities both prior to and following the rating revision. The bankruptcy probabilities are significantly decreased in the three months preceding the rating changes for the firms whose credit ratings are upgraded. In contrast, Delianedis and Geske (1998) found significantly different between risk neutral probabilities of default and the median baseline more than 10 month in advance to both credit rating upgrade and downgrade event. Nevertheless, our results also support the second hypothesis. There is

asymmetry of statistically significant between credit rating downgrades and credit rating upgrades. Although the directions of risk neutral probabilities of default changes before the credit rating revision are consistent with the first hypothesis, credit rating downgrades are only statistically significant both mean and median. Moreover, following the credit rating downgrades, the average firm experiences a significant increase in risk neutral probabilities of default while there is no significantly change following the credit rating upgrades. The results are thus consistent with the hypothesis that there is asymmetry market response between credit rating upgrade and credit rating downgrade.

4.3 Rating Prediction

Table 6 Panel A reports the results of an ordered probit model used to estimate rating categories on an annually basis. The dependent variable is 17 rating categories from AAA till CCC+. The independent variables are the level of the six chosen firm characteristics along with risk neutral probabilities of default calculated from Merton's model during the previous year (at time $t-1$). Positive coefficients imply that a higher level of the variable is associated with a stronger rating.

The coefficient estimates show that except for debt ratio and times interest earned, all of the variables have the expected sign and are statistically significant predictors of credit rating at 99% confident level. Market capitalization and return on assets are positively related to ratings quality while beta and long-term debt to assets ratio are negatively related to ratings quality. Risk neutral probabilities of default are also statistically significant for rating prediction. Lower risk neutral probabilities of default, which indicate better creditworthiness, are associated with higher credit rating.

Although *Pseudo-R*² provided in Table 6 Panel A gives a measure of the goodness of fit of the model, looking at the prediction table in Table 6 Panel B, which establishes the proportion of correctly prediction for each rating, is more precise. There is many rating that the model can't correctly predict while a few ratings are perfectly predicted. Prediction error is 55%. The result is varying because the ordered probit model tries to maximize the probabilities for the rating category that have maximum observation. To solve this problem, the rating categories must be classified into groups to balance the number of observation in each rating group. Table 7 Panel A shows the result of rating prediction model which rating categories had been classified into 4 groups. The dependent variable is 4 if firm has a rating by S&P of AAA and AA, 3 if A, 2 if BBB and 1 if below BBB. The coefficient did not differ from the result in Table 6 Panel A, especially the sign of the coefficient. Moreover, the result in Table 7 Panel B shows the better proportion of correctly predict from each rating groups in the sample. The prediction error had been reduced to 15%.

4.4 Rating Change Prediction

Moving from the rating prediction to rating changes prediction, whether or not firm's credit rating will upgrades and will downgrades during each year was predicted. The explanatory variables are based on Bond Quality Rating Change model (BQRC) by Bhandari, Soldofsky and Boe (1983), along with differences in market capitalization, firm beta, and firm's risk neutral probabilities of default between the previous year (at time t-1) and the two previous year (at time t-2).

Instead of showing the thirty binary probit regressions for each estimation period of credit rating upgrades and credit rating downgrades, Table 8 and Table 9 sum up the coefficient and p-value of chosen variables in each model for each

estimation period in credit rating upgrades prediction and credit rating downgrades prediction, respectively (Panel A: BQRC model, Panel B: Adjusted BQRC model, Panel C: Adjusted BQRC model with risk neutral probabilities of default). The results show that debt ratio is significant variables for all estimation period and model in credit rating changes prediction model. Other variables that significantly related to credit rating changes prediction depend on the estimation period and model.

With five estimation periods, we can perform the five year out-of-sample test for each rating changes prediction model and then measuring the result by using ROC curve. ROC curves from upgrade and downgrade predictions for each model are shown in Figure 4, 5, 6, 7, 8, and 9. The adjusted BQRC models have higher areas than the original BQRC model. Included risk neutral probabilities of default into adjusted BQRC model can also increase areas under ROC curve. In Figure 10, the adjusted BQRC models outperform the original BQRC models and show significantly difference between the areas under 2 ROC curves at 90% significant level for credit rating upgrades prediction. With risk neutral probabilities of default, the model has higher areas and significantly differs from the adjusted BQRC model at 95% significant level. Comparison of ROC curve for credit rating downgrades prediction is shown in Figure 11. Adjusted BQRC and adjusted BQRC with RNP model also have superior areas than original BQRC model but adjusted BQRC model is not statically difference. The adjusted BQRC with risk neutral probabilities of default still outperforms the adjusted BQRC model and significantly differs at 99% significant level. Figure 12 present comparison of credit rating upgrade prediction and credit rating downgrade prediction by adjusted BQRC model with risk neutral probabilities of default. Credit rating upgrade prediction outperforms credit rating downgrade prediction at the lower level of the cutoff point (or the higher proportion of correctly

prediction). Both perform proper the same at high level of cutoff point. Since credit rating upgrade and credit rating downgrade use different classification criteria, comparison of areas under independent ROC curves is used to test the statistical significance of the difference between them. The result indicates that two areas are not significantly different. So, we can not conclude that which credit rating upgrades or credit rating downgrades are more easily to predict.



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CHAPTER V

Conclusion and Recommendation

5.1 Conclusion

This thesis provides new empirical evidence on the relationship between risk neutral probabilities of default and credit rating changes. This study tests how risk neutral probabilities of default changes around credit rating changes and whether risk neutral probabilities of default are useful predictor for credit rating prediction and credit rating changes prediction.

The empirical results show that firm's estimated risk neutral probabilities of default decrease prior to, but not following credit rating upgrades. Credit rating downgrades, on the other hand, have been found that firm's estimated risk neutral probabilities of default significantly increase both before and after the credit rating changes. This result implies that credit rating downgrades are timelier and more informative than credit rating upgrades. Credit rating downgrades happen when firm's risk neutral probabilities of default increase significantly and the information from downgrades affect significant changes in risk neutral probabilities of default after the event. The result also supports the evidence from previous studies (e.g. Holthausen and Leftwich, 1986) that have found differently response to credit rating upgrades and downgrades by stock market. Firm's stock prices do not react to credit rating upgrades announcements, but negative stock returns existed when credit rating downgrades was announced.

This study also finds the usefulness of risk neutral probabilities of default as credit rating predictor and credit rating changes predictor. The result from the ordered probit model, applied for credit rating prediction, indicate that risk neutral probabilities of default have significant negative impact on firm's credit rating.

Increases in risk neutral probabilities of default will lead to lower credit rating categories. In addition, the ROC curve, applied for measure the predictive power of the rating changes prediction model, also indicated that including risk neutral probabilities of default into both credit rating upgrades prediction and credit rating downgrades prediction models statistically significant increase the predictive power of the models.

5.2 Recommendation

This thesis provides new evidence for the relationship between credit rating changes and changes in firm's risk neutral probabilities of default. However, risk neutral probabilities of default from Merton's model, which assume normal distribution for credit risk, are suitable for theoretical situation such as pricing the theoretical value for credit derivative. Credit rating changes are real situations so EDF provided by Moody's KMV which used actual default rate and estimated default point to determine the credit default probabilities are more suitable than risk neutral probabilities of default to predict for credit ratings and credit rating changes. Furthermore, there are still rooms for future research about the conflicts of interests between firms and rating agencies. Rating agencies receive the majority of their revenues from the companies they rate. These conflicts may deteriorate the rating prediction model.

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Table 1 Sample Description

This table shows the number of firm's rating in S&P500 index during the period from 1996 to 2006. The vast majority of firms in S&P500 index was rated investment grade (i.e. rating of BBB- or better) while the lowest rating is CCC+. The column "Scale" shows the rating class numerical value.

Scale	S&P Rating	Year										
		1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
17	AAA	11	10	9	9	10	10	8	8	7	5	5
16	AA+	7	7	5	4	3	1	1	1	1	1	1
15	AA	17	13	13	14	13	12	13	10	10	12	11
14	AA-	22	21	23	22	21	24	16	15	13	12	15
13	A+	42	46	47	45	48	45	46	43	42	43	43
12	A	70	71	71	78	79	75	75	76	72	71	70
11	A-	42	42	41	38	40	44	43	48	54	55	49
10	BBB+	45	46	50	52	56	60	56	57	57	65	65
9	BBB	30	34	31	35	39	52	60	64	66	63	69
8	BBB-	17	19	20	23	28	27	31	27	34	37	34
7	BB+	14	12	12	14	15	19	23	27	23	14	18
6	BB	13	14	12	13	16	16	13	12	13	14	22
5	BB-	6	7	7	8	6	4	8	11	11	14	12
4	B+	4	3	2	0	1	4	8	8	12	10	10
3	B	1	1	3	3	3	2	4	6	5	7	7
2	B-	1	1	1	0	1	0	2	2	1	0	0
1	CCC+	0	0	0	1	0	1	0	0	0	0	0
N/A	N/A	89	84	84	72	52	35	24	16	10	8	0
Total		431	431	431	431	431	431	431	431	431	431	431

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Table 2 Matrix of Old and New Ratings

This table shows old and new credit ratings of 693 credit rating change for sample in S&P500 from 1997 through 2006. The sample consists of 404 downgrades and 289 upgrades.

New Rating	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	Total
Old Rating																		
AAA	80		6	1														87
AA+		25	1	5														31
AA			109	10	6			1	1									127
AA-			2	150	28	7	1		1									189
A+			2	10	375	44	12	2	2									447
A					30	640	46	11	6	5								738
A-					1	37	356	36	14	2	1							447
BBB+						2	26	461	35	10	4	2	1	2	1			544
BBB							3	40	392	28	7	2	2					474
BBB-							1	3	40	192	17	6	1	1	1	1		263
BB+								6	29	128	6	1	2	1	1			173
BB									2	13	110	6	4	1				136
BB-									1	3	11	60	4	3				82
B+								1			3	12	34	2				52
B												1	4	28	2			35
B-												1	1	2	3		2	9
CCC+															1	1	0	2

Table 3 Summary Statistics Variables by Rating

This table presents the financial information and market variables used to measure the rating prediction. The mean, median, max, min, standard deviation, coefficient of skewness, and coefficient of kurtosis values for market capitalization, beta, total debt to assets ratio, long-term debt to assets ratio, interest coverage ratio, return on assets, and probabilities of default (PD) are presented by rating category in panel A, B, C, D, E, F, and G, respectively. Intuitively, the higher ratings are larger, less betas, have higher interest coverage, and are more profitable. Poorly rated firms have higher betas and greater PD indicating a higher risk of default.

Panel A: Mean

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	62,640,223	0.76	0.11	0.06	51.73	0.10	0.03
AA+	46,250,902	0.90	0.08	0.05	46.80	0.09	0.05
AA	37,226,891	0.78	0.18	0.10	20.22	0.09	0.24
AA-	27,403,848	0.85	0.24	0.12	15.00	0.07	1.23
A+	22,482,250	0.86	0.22	0.14	21.93	0.06	1.01
A	15,745,616	0.88	0.23	0.16	14.92	0.06	1.45
A-	14,011,697	0.89	0.26	0.18	15.88	0.05	1.15
BBB+	13,806,653	0.88	0.25	0.20	12.54	0.05	1.73
BBB	11,498,086	0.90	0.30	0.25	10.52	0.04	2.41
BBB-	10,427,447	1.08	0.28	0.24	7.83	0.04	3.41
BB+	7,401,274	1.09	0.31	0.26	10.44	0.04	4.99
BB	7,272,843	1.19	0.37	0.30	12.91	0.03	9.78
BB-	7,942,119	1.64	0.30	0.25	11.22	0.03	10.74
B+	7,053,740	1.89	0.34	0.25	4.50	0.01	10.08
B	7,444,860	1.91	0.34	0.27	0.83	-0.01	17.97
B-	6,470,517	1.76	0.58	0.48	-0.31	0.04	18.21
CCC+	2,690,854	1.14	0.47	0.43	3.08	0.04	18.68

Panel B: Median

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	36,749,820	0.75	0.04	0.02	27.05	0.12	0.00
AA+	28,446,361	0.77	0.08	0.04	15.64	0.10	0.00
AA	28,009,840	0.79	0.11	0.08	11.91	0.09	0.00
AA-	17,999,310	0.75	0.14	0.09	9.26	0.07	0.00
A+	13,146,135	0.83	0.16	0.12	7.74	0.06	0.00
A	9,047,445	0.82	0.16	0.13	7.45	0.05	0.00
A-	8,002,161	0.86	0.21	0.16	6.37	0.04	0.00
BBB+	7,293,930	0.80	0.22	0.18	5.12	0.04	0.01
BBB	6,206,670	0.88	0.28	0.23	3.92	0.04	0.02
BBB-	6,135,807	1.03	0.27	0.23	3.76	0.04	0.22
BB+	4,642,049	1.05	0.31	0.26	3.65	0.03	0.29
BB	3,072,129	1.16	0.38	0.31	2.64	0.02	1.37
BB-	2,814,078	1.47	0.23	0.21	2.28	0.03	3.36
B+	2,081,912	2.07	0.28	0.17	1.43	0.00	3.06
B	1,377,620	1.73	0.26	0.24	0.43	0.01	10.14
B-	1,102,930	1.68	0.64	0.56	0.25	0.05	7.79
CCC+	690,854	1.14	0.47	0.43	3.08	0.04	18.68

Table 3 Summary Statistics Variables by Rating (Continue)

Panel C: Max

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	82,640,223	0.96	0.11	0.06	56.73	0.10	0.04
AA+	56,250,902	0.90	0.08	0.05	46.80	0.09	0.05
AA	37,226,891	0.78	0.18	0.10	20.22	0.09	0.24
AA-	27,403,848	0.85	0.24	0.12	15.00	0.07	1.23
A+	26,482,250	0.86	0.22	0.14	21.93	0.06	1.01
A	15,745,616	0.88	0.23	0.16	14.92	0.06	1.45
A-	14,011,697	0.89	0.26	0.18	15.88	0.05	1.15
BBB+	13,806,653	0.88	0.25	0.20	12.54	0.05	1.73
BBB	11,498,086	0.90	0.30	0.25	10.52	0.04	2.41
BBB-	12,427,447	1.08	0.28	0.24	7.83	0.04	3.41
BB+	7,801,274	1.09	0.31	0.26	10.44	0.04	4.99
BB	7,572,843	1.19	0.37	0.30	12.91	0.03	9.78
BB-	7,942,119	1.64	0.30	0.25	11.22	0.03	10.74
B+	9,053,740	1.89	0.34	0.25	4.50	0.01	10.08
B	7,444,860	1.91	0.34	0.27	0.83	-0.01	17.97
B-	6,470,517	1.76	0.58	0.48	-0.31	0.04	18.21
CCC+	2,690,854	1.14	0.47	0.43	3.08	0.04	18.68

Panel D: Min

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	3,344,606	-0.31	0.00	0.00	2.31	0.01	0.00
AA+	2,415,817	-0.13	0.00	0.00	0.80	0.03	0.00
AA	1,976,084	-0.53	0.00	0.00	0.65	0.00	0.00
AA-	1,513,522	-0.35	0.00	0.00	-3.96	-0.05	0.00
A+	1,241,278	-0.54	0.00	0.00	-14.77	-0.09	0.00
A	431,528	-0.47	0.00	0.00	-10.50	-0.14	0.00
A-	467,090	-0.60	0.00	0.00	-12.01	-0.16	0.00
BBB+	379,949	-0.72	0.00	0.00	-49.89	-0.04	0.00
BBB	336,876	-0.66	0.00	0.00	-38.94	-0.16	0.00
BBB-	317,781	-0.63	0.00	0.00	-43.20	-0.16	0.00
BB+	353,438	-0.54	0.00	0.00	-14.20	-0.23	0.00
BB	285,661	-0.67	0.00	0.00	-27.72	-0.07	0.00
BB-	451,813	-0.20	0.00	0.00	-22.11	-0.22	0.00
B+	455,196	-0.40	0.00	0.00	-31.45	-0.25	0.00
B	442,213	0.47	0.02	0.02	-16.72	-0.23	0.00
B-	233,426	-0.35	0.24	0.21	-10.25	-0.03	0.34
CCC+	197,834	0.71	0.38	0.36	3.06	0.03	5.59

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Table 3 Summary Statistics Variables by Rating (Continue)

Panel E: Standard Deviation

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	61,674,768	0.45	0.15	0.08	40.00	6.02	0.20
AA+	17,548,969	0.44	0.08	0.07	80.99	3.12	0.14
AA	37,258,629	0.46	0.18	0.09	27.79	5.27	1.87
AA-	31,042,849	0.5	0.21	0.10	17.73	5.65	3.76
A+	40,227,804	0.57	0.18	0.10	63.42	5.04	4.13
A	23,196,526	0.56	0.19	0.12	32.24	5.04	5.30
A-	17,537,176	0.6	0.18	0.12	45.97	5.07	4.07
BBB+	22,601,939	0.65	0.17	0.13	26.81	4.93	5.55
BBB	15,747,647	0.63	0.18	0.16	31.79	4.64	8.23
BBB-	20,368,546	0.7	0.18	0.15	12.66	4.72	7.42
BB+	7,910,180	0.82	0.20	0.16	28.17	5.40	10.94
BB	10,179,441	0.8	0.21	0.16	47.71	5.02	16.75
BB-	19,806,488	1	0.23	0.20	25.09	7.98	14.44
B+	11,878,364	1.02	0.24	0.20	13.78	8.72	19.11
B	6,506,048	0.91	0.25	0.19	7.24	6.46	21.89
B-	5,244,563	1.45	0.17	0.16	3.76	7.81	25.19
CCC+	1,079,073	0.6	0.12	0.10	0.03	1.31	18.52

Panel F: Coefficient of Skewness

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	1.06	-0.22	1.75	2.00	3.05	-0.06	478.35
AA+	1.73	0.20	3.04	4.03	2.63	-0.96	374.35
AA	1.64	-0.03	1.60	2.22	3.70	0.78	1112.22
AA-	2.51	0.15	1.02	1.58	3.30	0.47	386.32
A+	2.46	0.34	1.15	0.75	6.71	0.95	645.40
A	4.32	0.46	1.27	1.15	8.08	1.57	672.71
A-	2.88	0.47	0.73	0.76	7.78	0.87	642.78
BBB+	4.21	0.65	0.78	0.61	5.32	2.07	561.08
BBB	3.90	0.44	0.37	0.35	11.11	0.36	662.34
BBB-	5.31	0.38	0.50	0.42	3.03	0.66	338.01
BB+	2.94	0.50	0.28	0.27	6.45	-0.41	336.87
BB	3.03	0.43	0.27	0.06	8.47	0.92	200.97
BB-	3.12	0.45	0.50	0.54	2.84	0.08	133.82
B+	3.40	-0.36	0.33	0.67	2.33	0.06	317.76
B	1.45	0.46	0.61	0.54	1.00	-1.72	145.86
B-	1.16	-0.21	-1.06	-0.91	-2.41	1.43	223.57
CCC+	N/A	N/A	N/A	N/A	N/A	N/A	N/A

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Table 3 Summary Statistics Variables by Rating (Continue)

Panel G: Coefficient of Kurtosis

<i>Rating</i>	<i>Market Capital</i>	<i>Beta</i>	<i>Total Debt/Asset</i>	<i>Long-Term Debt/Assets</i>	<i>Interest Coverage</i>	<i>Return on Assets</i>	<i>Probabilities of Default</i>
AAA	-0.11	-0.46	1.73	2.97	12.88	-1.31	2501.97
AA+	2.30	0.14	13.20	19.48	6.11	-0.36	1521.31
AA	3.14	0.09	1.60	5.65	16.96	0.43	13021.35
AA-	7.83	-0.60	-0.28	2.85	14.57	-0.39	1503.60
A+	6.20	0.31	0.80	-0.17	50.26	1.48	4763.71
A	24.96	0.42	0.98	1.19	92.95	12.06	6132.96
A-	9.55	0.30	-0.44	0.29	71.52	2.89	5487.46
BBB+	20.06	0.52	0.17	-0.25	35.48	10.29	4018.86
BBB	19.34	0.70	-0.49	-0.70	165.15	1.88	5266.28
BBB-	35.24	0.37	-0.26	-0.51	16.62	3.06	1288.20
BB+	13.11	-0.21	-0.83	-0.89	48.23	4.53	1237.12
BB	11.11	0.45	-0.70	-0.72	86.61	1.14	299.72
BB-	10.60	-0.50	-0.97	-0.81	8.00	1.92	59.58
B+	14.64	-0.91	-1.37	-0.91	11.20	2.27	1078.51
B	1.30	-0.77	-0.86	-0.73	4.19	4.46	158.70
B-	0.79	-1.30	0.13	-0.34	6.53	2.47	540.97
CCC+	N/A	N/A	N/A	N/A	N/A	N/A	N/A

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Table 4 Summary Statistics Variables by Rating Changes Group

This table presents the financial information and market variables used to measure the rating change prediction. The mean, median, max, min, standard deviation, coefficient of skewness, and coefficient of kurtosis values for times interest earned ratio, times interest earned trend, total debt to assets ratio, total debt to assets ratio trend, return on assets, return on assets trend, residual of return on assets trend, market capitalization change, beta change, and probabilities of default change are presented by firm's rating changes group in panel A, B, C, D, E, F, and G, respectively. Intuitively, the upgraded firms are larger, have negative debt ratio trend, have positive interest coverage trend, and have positive profitability trend. Downgraded firms have higher betas, greater earnings instability and greater PD indicating a higher risk of default.

Panel A: Mean

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	11.10	1.28	0.62	-0.01	6.31
No Changed	10.84	-0.80	0.64	0.00	5.49
Downgraded	5.27	-19.36	0.69	0.01	3.31

	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	0.61	1.34	0.20	0.00	-0.45
No Changed	0.06	1.55	0.12	0.01	-0.26
Downgraded	-0.49	1.80	-0.05	0.10	1.46

Panel B: Median

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	6.54	0.68	0.60	-0.01	5.88
No Changed	6.34	0.11	0.63	0.00	4.64
Downgraded	3.62	-0.40	0.69	0.01	2.53

	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	0.49	1.11	0.18	-0.01	-0.14
No Changed	0.03	1.20	0.12	0.02	-0.17
Downgraded	-0.37	1.34	-0.02	0.06	0.79

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Table 4 Summary Statistics Variables by Rating Changes Group (Continue)

Panel C: Max

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	73.78	23.44	0.94	0.08	18.98
No Changed	107.15	60.52	0.95	0.12	19.42
Downgraded	42.10	8.79	0.94	0.13	14.02
	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	4.70	6.52	2.56	2.12	16.38
No Changed	9.97	12.97	2.47	2.31	22.11
Downgraded	4.62	12.40	1.80	2.87	20.58

Panel D: Min

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	-1.92	-18.78	0.29	-0.16	-2.03
No Changed	-4.56	-25.57	0.27	-0.20	-4.78
Downgraded	-4.75	-42.24	0.28	-0.08	-5.78
	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	-2.73	0.04	-1.21	-3.47	-18.69
No Changed	-4.84	0.01	-3.03	-3.54	-23.49
Downgraded	-5.68	0.03	-2.24	-2.05	-16.64

Panel E: Standard Deviation

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	12.47	3.61	0.17	0.03	4.42
No Changed	13.14	17.68	0.16	0.03	4.10
Downgraded	5.89	30.64	0.14	0.03	3.79
	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	1.17	1.47	0.40	0.61	0.03
No Changed	1.00	1.49	0.35	0.54	0.03
Downgraded	1.04	1.59	0.49	0.58	0.04

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Table 4 Summary Statistics Variables by Rating Changes Group (Continue)

Panel F: Coefficient of Skewness

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	2.31	1.10	0.17	-0.72	0.37
No Changed	2.84	-4.65	0.05	-0.18	0.65
Downgraded	2.25	-9.00	-0.35	0.31	0.75

	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	0.49	1.32	0.77	-0.73	0.16
No Changed	0.36	2.12	-0.01	-0.40	0.11
Downgraded	-0.39	2.18	-0.84	0.32	0.79

Panel G: Coefficient of Kurtosis

Rating Changes Group	Times Interest Earned	Times Interest Earned Trend	Total Debt/Assets Ratio	Total Debt/Assets Trend	Return on Assets
Upgraded	5.80	13.60	-0.89	4.76	-0.75
No Changed	10.04	30.46	-0.82	4.62	-0.25
Downgraded	7.03	40.27	-0.35	2.04	0.25

	Return on Assets Trend	Residual of Return on Assets Trend	Market Capital Change	Beta Change	Probabilities of Default Change
Upgraded	1.67	1.18	5.18	4.81	8.95
No Changed	5.80	7.04	5.23	3.29	6.64
Downgraded	3.43	7.64	2.54	2.52	2.79

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Table 5 Changes in probabilities of default around credit rating changes

This table presents monthly changes in sample firm's risk neutral probabilities of default around the credit rating revisions. The monthly change in the risk neutral probabilities of default is compute by current month-end risk neutral probabilities of default minus previous month-end risk neutral probabilities of default. p-value indicate significant levels for two-tailed tests. The table reports risk neutral probabilities of default changes for a sample of 693 rating changes with 404 downgrades and 289 upgrades.

	Upgrades			
	Mean	T-test p-value	Median	Wilcoxon Test p-value
Month -3	0.0050%	0.9420	-0.0391%	0.3957
Month -2	-0.1219%	0.4837	-0.0439%	0.3604
Month -1	-0.0387%	0.3667	-0.0540%	0.0956 ^c
Month 0	0.0250%	0.6492	-0.0312%	0.3044
Month +1	0.0190%	0.6486	-0.0018%	0.1473
Month +2	0.0954%	0.2187	-0.0130%	0.6871
Month +3	-0.0695%	0.1352	-0.0275%	0.6109
	Downgrades			
	Mean	T-test p-value	Median	Wilcoxon Test p-value
Month -3	0.2569%	0.5662	0.0768%	0.4686
Month -2	0.2453%	0.0025 ^a	0.0140%	0.0017 ^a
Month -1	0.2108%	0.0006 ^a	0.0247%	0.0586 ^c
Month 0	0.3063%	0.0076 ^a	0.0075%	0.0174 ^b
Month +1	0.8174%	0.0006 ^a	0.0805%	0.0590 ^c
Month +2	0.0914%	0.2714	-0.0039%	0.5204
Month +3	0.2047%	0.1864	0.0424%	0.0401 ^b
a	Indicates significance at the 99% confidence level			
b	Indicates significance at the 95% confidence level			
c	Indicates significance at the 90% confidence level			

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Table 6 Credit Rating Prediction – All Ratings

Credit rating predictions are provided for an ordered probit model where the dependent variable is the rating category and the independent variables are shown in the table. The estimation period is ten years from 1997 to 2006. Better ratings are represented by higher numerical number so positive coefficient implies that greater value of the independents variable is associated with better rating assignment. The limit points define a range of values corresponding to each observed rating category. The ordered probit model also provides the expectation-prediction table as shown in Panel B for classify the observations on the basis of the predicted response.

Panal A : Estimation Output				
	Coefficient	Std. Error	z-Statistic	Prob.
Market Capitalization	0.314338	0.031300	26.3837	0.0000 ^a
Beta	-0.434554	0.054790	-12.6785	0.0000 ^a
Total Debt to Assets	2.363531	0.252888	13.7086	0.0000 ^a
Long-Term Debt to Assets	-5.369315	0.359406	-21.5288	0.0000 ^a
Interest Coverage Ratio	-0.000194	0.000024	-2.2058	0.0274 ^b
Return on Assets	0.021671	0.800027	5.0700	0.0000 ^a
Probabilities of Default	-2.641979	0.510367	-5.6718	0.0000 ^a
Limit Points				
LIMIT_2:C(8)	0.034253	0.429104	2.3555	0.0185 ^b
LIMIT_3:C(9)	0.461493	0.335134	5.9672	0.0009 ^a
LIMIT_4:C(10)	1.033882	0.311846	11.0097	0.0000 ^a
LIMIT_5:C(11)	1.474622	0.302999	13.1952	0.0000 ^a
LIMIT_6:C(12)	1.911735	0.296772	15.1439	0.0000 ^a
LIMIT_7:C(13)	2.298780	0.294042	16.8726	0.0000 ^a
LIMIT_8:C(14)	2.682800	0.294352	18.2219	0.0000 ^a
LIMIT_9:C(15)	3.101571	0.294076	19.6215	0.0000 ^a
LIMIT_10:C(16)	3.668290	0.293955	21.4968	0.0000 ^a
LIMIT_11:C(17)	4.149402	0.293807	23.0623	0.0000 ^a
LIMIT_12:C(18)	4.543860	0.294844	24.1801	0.0000 ^a
LIMIT_13:C(19)	5.236377	0.297423	26.0376	0.0000 ^a
LIMIT_14:C(20)	5.847387	0.300401	27.7026	0.0000 ^a
LIMIT_15:C(21)	6.244786	0.304235	28.8768	0.0000 ^a
LIMIT_16:C(22)	6.745690	0.310226	30.3377	0.0000 ^a
LIMIT_17:C(23)	6.897875	0.306709	31.3860	0.0000 ^a
Akaike info criterion	4.193388	Schwarz criterion		4.23731
Log likelihood	-6634.004	Hannan-Quinn criter.		4.209141
Restr. log likelihood	-7363.269	Avg. log likelihood		-2.08945
LR statistic (7 df)	1458.530	LR index (Pseudo-R2)		0.099041
Probability(LR stat)	0.000000			

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

Table 6 Credit Rating Prediction – All Ratings (continue)

Panel B : Prediction Table						
Ratings	Value	Count	Count of obs with Max Prob	Error	Sum of all Probabilities	Error
CCC+	1	2	2	0	3.221	-1.221
B-	2	4	0	4	5.206	-1.206
B	3	13	12	1	15.629	-2.629
B+	4	26	0	26	27.771	-1.771
BB-	5	57	24	33	54.43	2.57
BB	6	90	9	81	85.327	4.673
BB+	7	136	18	118	134.954	1.046
BBB-	8	224	4	220	220.251	3.749
BBB	9	436	915	-479	430.046	5.954
BBB+	10	459	102	357	459.2	-0.2
A-	11	400	0	400	399.55	0.45
A	12	619	1901	-1282	628.18	-9.18
A+	13	369	171	198	380.322	-11.322
AA-	14	151	0	151	151.129	-0.129
AA	15	112	0	112	106.83	5.17
AA+	16	20	0	20	19.141	0.859
AAA	17	57	17	40	53.813	3.187

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Table 7 Credit Rating Prediction – Group Ratings

Credit rating predictions are provided for an ordered probit model where the dependent variable is the rating category and the independent variables are shown in the table. The estimation period is ten years from 1997 to 2006. Better ratings are represented by higher numerical number so positive coefficient implies that greater value of the independents variable is associated with better rating assignment. The limit points define a range of values corresponding to each observed rating category. The ordered probit model also provides the expectation-prediction table as shown in Panel B for classify the observations on the basis of the predicted response.

Panel A : Estimation Output				
	Coefficient	Std. Error	z-Statistic	Prob.
Market Capitalization	0.315897	0.019892	15.8804	0.0000 ^a
Beta	-0.422473	0.037295	-11.3279	0.0000 ^a
Total Debt to Assets	2.641651	0.239988	11.0075	0.0000 ^a
Long-Term Debt to Assets	-5.868118	0.311170	-18.8582	0.0000 ^a
Interest Coverage Ratio	-0.000545	0.000710	-2.9889	0.0028 ^a
Return on Assets	0.018582	0.005221	3.5401	0.0004 ^a
Probabilities of Default	-2.992475	0.442347	-6.7650	0.0000 ^a
Limit Points				
LIMIT_2:C(8)	2.649132	0.322543	8.2133	0.0000 ^a
LIMIT_3:C(9)	4.136587	0.323063	12.8043	0.0000 ^a
LIMIT_4:C(10)	5.835099	0.329477	17.7102	0.0000 ^a
Akaike info criterion	2.002842	Schwarz criterion		2.021939
Log likelihood	-3169.512	Hannan-Quinn criter.		2.009691
Restr. log likelihood	-3819.642	Avg. log likelihood		-0.998272
LR statistic (7 df)	1300.260	LR index (Pseudo-R2)		0.170207
Probability(LR stat)	0.000000			
<ul style="list-style-type: none"> a Indicates significance at the 99% confidence level b Indicates significance at the 95% confidence level c Indicates significance at the 90% confidence level 				

Panel B : Prediction Table						
Ratings	Value	Count of obs			Sum of all	
		Count	with Max Prob	Error	Probabilities	Error
below BBB	1	328	130	198	328.485	-0.485
BBB	2	1119	1098	21	1111.238	7.762
A	3	1388	1879	-491	1399.597	-11.597
AAA&AA	4	340	68	272	335.68	4.32

Table 8 Credit Rating Upgrades Prediction

Credit rating upgrades predictions are provide for a binary probit model where the dependent variable is the rating change from the previous month (1 for upgrade, and 0 for other) and the independent variables are shown in the table. There are five estimation periods for five years out-of-sample test (from 2002 to 2006). Each test used five previous year data to model for credit rating upgrades prediction in each year. The coefficients of each variable in BQRC model, adjusted BQRC model, and adjusted BQRC model with risk neutral probabilities of default are shown in panel A, B, and C, respectively. p-values are also shown below each coefficient.

Panel A: BQRC Model

Variables	Estimation Period				
	1997-2001	1998-2002	1999-2003	2000-2004	2001-2005
Times Interest Earned	-0.017615 0.0219 ^b	-0.024583 0.0102 ^b	-0.034976 0.0048 ^a	-0.031211 0.0096 ^a	-0.024071 0.0079 ^a
Times Interest Earned Trend	0.000432 0.4663	0.003855 0.6650	0.00322 0.8277	0.009331 0.7389	0.024604 0.4192
Debt Ratio	-1.769648 0.0000 ^a	-2.038593 0.0000 ^a	-2.033114 0.0000 ^a	-2.087552 0.0000 ^a	-2.044938 0.0000 ^a
Debt Ratio Trend	-1.868901 0.3116	-1.666689 0.3941	-5.872452 0.0084 ^a	-6.376033 0.0061 ^a	-5.918246 0.0095 ^a
Return on Assets	-0.038327 0.0328 ^b	-0.014701 0.4361	-0.004782 0.8251	0.00301 0.8978	-0.006136 0.7579
Return on Assets Trend	0.268674 0.0003 ^a	0.220048 0.0011 ^a	0.261321 0.0001 ^a	0.257859 0.0004 ^a	0.26447 0.0001 ^a
Return on Assets Trend Residual	-0.035171 0.3429	-0.00151 0.9652	0.010403 0.7671	-0.013079 0.7429	0.013201 0.7379
Intercept	-1.759448 0.0000 ^a	-2.08732 0.0000 ^a	-2.359332 0.0000 ^a	-2.753058 0.0000 ^a	-2.086901 0.0000 ^a

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Table 8 Credit Rating Upgrades Prediction (Continue)

Panel B: Adjusted BQRC Model

<i>Variables</i>	<i>Estimation Period</i>				
	<i>1997-2001</i>	<i>1998-2002</i>	<i>1999-2003</i>	<i>2000-2004</i>	<i>2001-2005</i>
Times Interest Earned	-0.017737 0.0208 ^b	-0.024935 0.0106 ^b	-0.0341 0.0058 ^a	-0.030384 0.0118 ^b	-0.024382 0.0079 ^a
Times Interest Earned Trend	0.000132 0.3139	0.002111 0.7605	0.002154 0.8649	0.008041 0.7793	0.025821 0.4109
Debt Ratio	-1.891232 0.0000 ^a	-2.129084 0.0000 ^a	-2.03805 0.0000 ^a	-2.10793 0.0000 ^a	-2.122431 0.0000 ^a
Debt Ratio Trend	-1.38425 0.4991	-1.312457 0.5303	-6.58203 0.0053 ^a	-6.89987 0.0055 ^a	-6.183977 0.0090 ^a
Return on Assets	-0.0381 0.0387 ^b	-0.018365 0.3544	-0.007654 0.7322	0.000496 0.9836	-0.006369 0.7558
Return on Assets Trend	0.249718 0.0012 ^a	0.207486 0.0042 ^a	0.255906 0.0002 ^a	0.253648 0.0008 ^a	0.25472 0.0003 ^a
Return on Assets Trend Residual	-0.053233 0.1688	-0.014897 0.6827	-0.003178 0.9309	-0.032076 0.4485	0.009475 0.8167
Market Capitalization Changes	0.478941 0.0003 ^a	0.553822 0.0000 ^a	0.401432 0.0028 ^a	0.40426 0.0037 ^a	0.408517 0.0050 ^a
Beta Changes	0.053771 0.5547	0.008675 0.9378	0.066631 0.5697	0.022109 0.8482	0.095421 0.3741
Intercept	-1.826067 0.0000 ^a	-2.356024 0.0000 ^a	-2.73701 0.0000 ^a	-3.159161 0.0000 ^a	-2.330991 0.0000 ^a

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Table 8 Credit Rating Upgrades Prediction (Continue)

Panel C: Adjusted BQRC Model with RNP

<i>Variables</i>	<i>Estimation Period</i>				
	<i>1997-2001</i>	<i>1998-2002</i>	<i>1999-2003</i>	<i>2000-2004</i>	<i>2001-2005</i>
Times Interest Earned	-0.017557 0.0254 ^b	-0.023865 0.0135 ^b	-0.033853 0.0058 ^a	-0.028202 0.0163 ^b	-0.021761 0.0161 ^b
Times Interest Earned Trend	9.13E-05 0.3646	0.000755 0.9261	0.002705 0.8439	0.005075 0.8566	0.024007 0.4427
Debt Ratio	-1.896903 0.0000 ^a	-2.105995 0.0000 ^a	-1.979551 0.0000 ^a	-2.086911 0.0000 ^a	-2.128078 0.0000 ^a
Debt Ratio Trend	-1.538678 0.4536	-1.451549 0.4934	-6.681708 0.0044 ^a	-7.031258 0.0054 ^a	-5.851613 0.0153 ^b
Return on Assets	-0.032389 0.0840 ^c	-0.013976 0.4847	-0.007849 0.7264	-0.002689 0.9125	-0.009392 0.6557
Return on Assets Trend	0.246815 0.0014 ^a	0.208155 0.0038 ^a	0.254805 0.0003 ^a	0.264409 0.0006 ^a	0.265684 0.0002 ^a
Return on Assets Trend Residual	-0.049441 0.2094	-0.013289 0.7185	-0.000881 0.9810	-0.03282 0.4483	0.008875 0.8326
Market Capitalization Changes	0.174528 0.2733	0.2299 0.1500	0.199319 0.2221	0.210741 0.2195	0.229388 0.2008
Beta Changes	0.068998 0.4696	0.032455 0.7776	0.092358 0.4385	0.012248 0.9165	0.087087 0.4189
Probabilities of Default Changes	-6.079649 0.0071 ^a	-6.167657 0.0042 ^a	-4.157747 0.0044 ^a	-3.51146 0.009 ^a	-3.085401 0.0013 ^a
Intercept	-1.818752 0.0000 ^a	-2.345706 0.0000 ^a	-2.731057 0.0000 ^a	-3.056527 0.0000 ^a	-2.296281 0.0000 ^a

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Table 9 Credit Rating Downgrades Prediction

Credit rating downgrades predictions are provide for a binary probit model where the dependent variable is the rating change from the previous month (1 for downgrade, and 0 for other) and the independent variables are shown in the table. There are five estimation periods for five years out-of-sample test (from 2002 to 2006). Each test used five previous year data to model for credit rating downgrades prediction in each year. The coefficients of each variable in BQRC model, adjusted BQRC model, and adjusted BQRC model with risk neutral probabilities of default are shown in panel A, B, and C, respectively. p-values are also shown below each coefficient.

Panel A: BQRC Model

Variables	Estimation Period				
	1997-2001	1998-2002	1999-2003	2000-2004	2001-2005
Times Interest Earned	-0.021597 0.0108 ^b	-0.031878 0.0071 ^a	-0.043384 0.0002 ^a	-0.015268 0.1804	-0.01014 0.2294
Times Interest Earned Trend	-0.002381 0.7673	-0.001742 0.8323	-0.000491 0.0000 ^a	0.000962 0.9541	0.006654 0.7224
Debt Ratio	-1.334788 0.0000 ^a	-1.254576 0.0000 ^a	-1.119063 0.0000 ^a	-1.200769 0.0000 ^a	-1.25694 0.0000 ^a
Debt Ratio Trend	8.254802 0.0000 ^a	7.711539 0.0000 ^a	6.993365 0.0001 ^a	7.724798 0.0001 ^a	8.653378 0.0000 ^a
Return on Assets	-0.047392 0.0046 ^a	-0.051793 0.0040 ^a	-0.029701 0.0828 ^c	-0.057445 0.0025 ^a	-0.064092 0.0003 ^a
Return on Assets Trend	-0.033416 0.5677	-0.028464 0.6048	-0.055295 0.2597	-0.03563 0.5073	-0.064158 0.2436
Return on Assets Trend Residual	-0.032002 0.3900	0.013094 0.6826	-0.03524 0.2376	-0.030948 0.2874	-0.011957 0.6964
Intercept	-1.205627 0.0001 ^a	-0.953877 0.0013 ^a	-0.971784 0.0007 ^a	-1.330853 0.0000 ^a	-1.604523 0.0000 ^a

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Table 9 Credit Rating Downgrades Prediction (Continue)

Panel B: Adjusted BQRC Model

Variables	Estimation Period				
	1997-2001	1998-2002	1999-2003	2000-2004	2001-2005
Times Interest Earned	-0.020325 0.0160 ^b	-0.028371 0.0113 ^b	-0.041929 0.0002 ^a	-0.01334 0.2407	-0.008822 0.3031
Times Interest Earned Trend	-0.004207 0.5776	-0.003934 0.6068	-0.000457 0.0000 ^a	0.012186 0.4846	0.016737 0.3970
Debt Ratio	-1.280758 0.0000 ^a	-1.239635 0.0000 ^a	-1.224797 0.0000 ^a	-1.301474 0.0000 ^a	-1.275361 0.0000 ^a
Debt Ratio Trend	7.391935 0.0003 ^a	7.20975 0.0002 ^a	7.261825 0.0001 ^a	8.511916 0.0000 ^a	9.3671 0.0000 ^a
Return on Assets	-0.043652 0.0105 ^b	-0.048354 0.0078 ^a	-0.02167 0.2108	-0.049036 0.0115 ^b	-0.056892 0.0013 ^a
Return on Assets Trend	-0.023374 0.6814	-0.026921 0.6180	-0.061945 0.2036	-0.054543 0.3184	-0.068201 0.2160
Return on Assets Trend Residual	-0.019473 0.6045	0.010851 0.7420	-0.047583 0.1361	-0.036103 0.2310	-0.025039 0.4347
Market Capitalization Changes	-0.795211 0.0000 ^a	-0.850097 0.0000 ^a	-0.760155 0.0000 ^a	-0.823944 0.0000 ^a	-0.89292 0.0000 ^a
Beta Changes	0.014459 0.8570	0.135188 0.1567	0.220978 0.0241 ^b	0.267285 0.0107 ^b	0.195295 0.0312 ^b
Intercept	-1.19555 0.0002 ^a	-1.06111 0.0009 ^a	-1.080767 0.0004 ^a	-1.332949 0.0000 ^a	-1.603483 0.0000 ^a

a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Table 9 Credit Rating Downgrades Prediction (Continue)

Panel C: Adjusted BQRC Model with RNPD

Variables	Estimation Period				
	1997-2001	1998-2002	1999-2003	2000-2004	2001-2005
Times Interest Earned	-0.020125 0.0148 ^b	-0.028252 0.0117 ^b	-0.043288 0.0002 ^a	-0.012512 0.2644	-0.008273 0.3313
Times Interest Earned Trend	-5.32E-04 0.0230 ^b	-0.000502 0.0049 ^a	-0.000471 0.0000 ^a	0.009983 0.5650	0.01465 0.4555
Debt Ratio	-1.284842 0.0000 ^a	-1.233923 0.0000 ^a	-1.222611 0.0000 ^a	-1.353103 0.0000 ^a	-1.295891 0.0000 ^a
Debt Ratio Trend	7.34306 0.0004 ^a	7.161624 0.0002 ^a	6.830189 0.0003 ^a	8.553243 0.0000 ^a	9.296501 0.0000 ^a
Return on Assets	-0.044132 0.0096 ^a	-0.04903 0.0073 ^a	-0.01983 0.2609	-0.04963 0.0110 ^b	-0.05702 0.0015 ^a
Return on Assets Trend	-0.01673 0.7565	-0.023001 0.6514	-0.068433 0.1664	-0.05429 0.3233	-0.070444 0.2043
Return on Assets Trend Residual	-0.026235 0.4971	0.00664 0.8430	-0.055197 0.0939 ^c	-0.03348 0.2708	-0.023717 0.4635
Market Capitalization Changes	-0.729537 0.0000 ^a	-0.840145 0.0000 ^a	-0.742121 0.0000 ^a	-0.674287 0.0000 ^a	-0.8228 0.0000 ^a
Beta Changes	0.010164 0.9018	0.139822 0.1512	0.210761 0.0336 ^b	0.274416 0.0097 ^a	0.204706 0.0249 ^b
Probabilities of Default Changes	1.133502 0.0098a	0.188001 0.0000a	0.492612 0.0000a	2.531975 0.0056a	0.991577 0.0000a
Intercept	-1.290548 0.0001 ^a	-1.122456 0.0005 ^a	-1.117887 0.0003 ^a	-1.355911 0.0000 ^a	-1.600397 0.0000 ^a

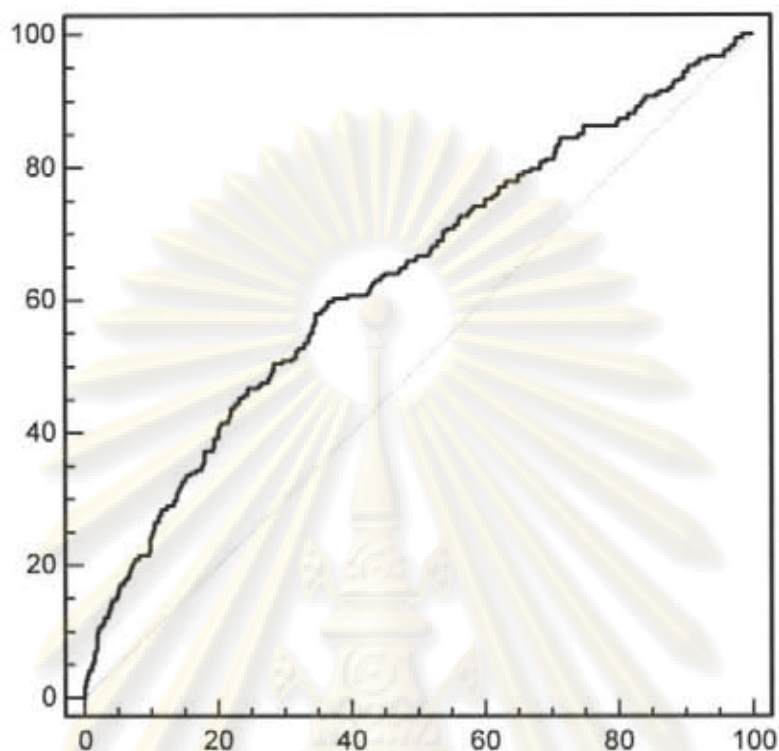
a Indicates significance at the 99% confidence level

b Indicates significance at the 95% confidence level

c Indicates significance at the 90% confidence level

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Figure 1 Example of ROC Curve



Area under the ROC curve (AUC)	0.635
Standard error	0.0214
95% Confidence interval	0.612 to 0.657
z statistic	6.295
Significance level P (Area=0.5)	0.0001

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Figure 2 Changes in RNPD around Credit Rating Upgrades

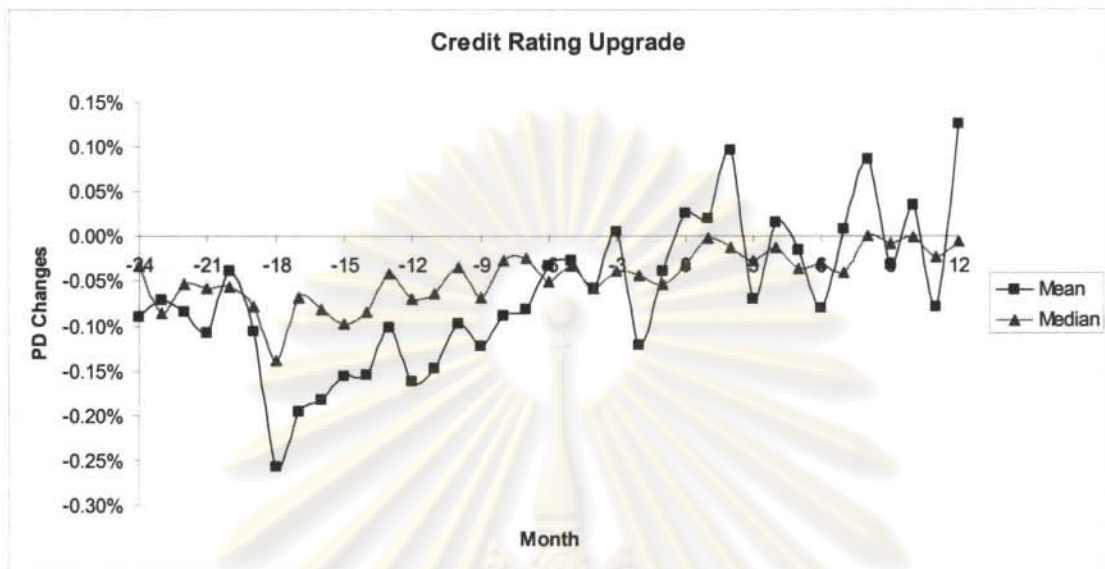
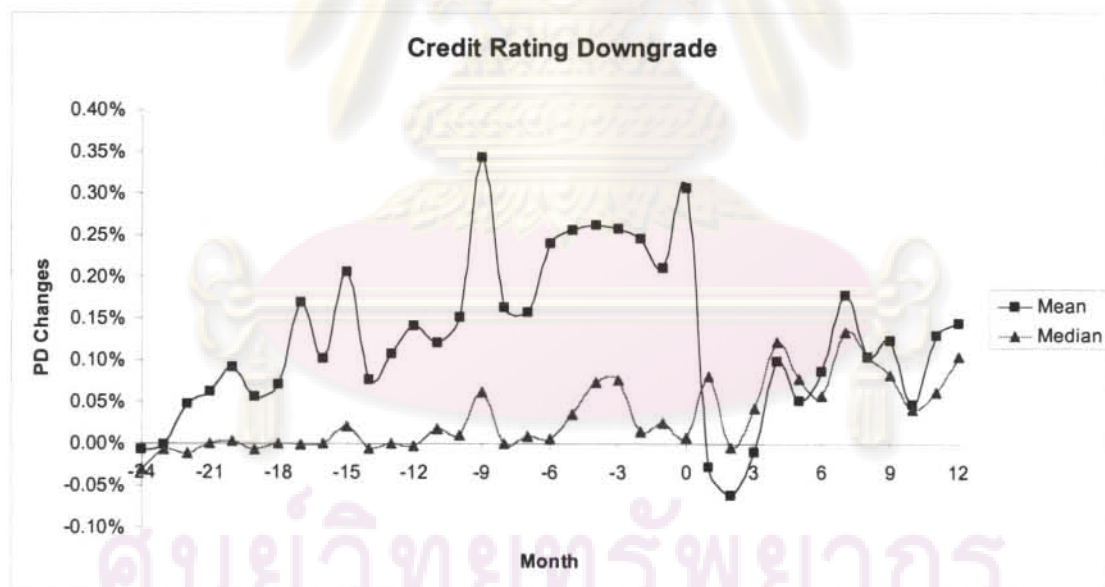
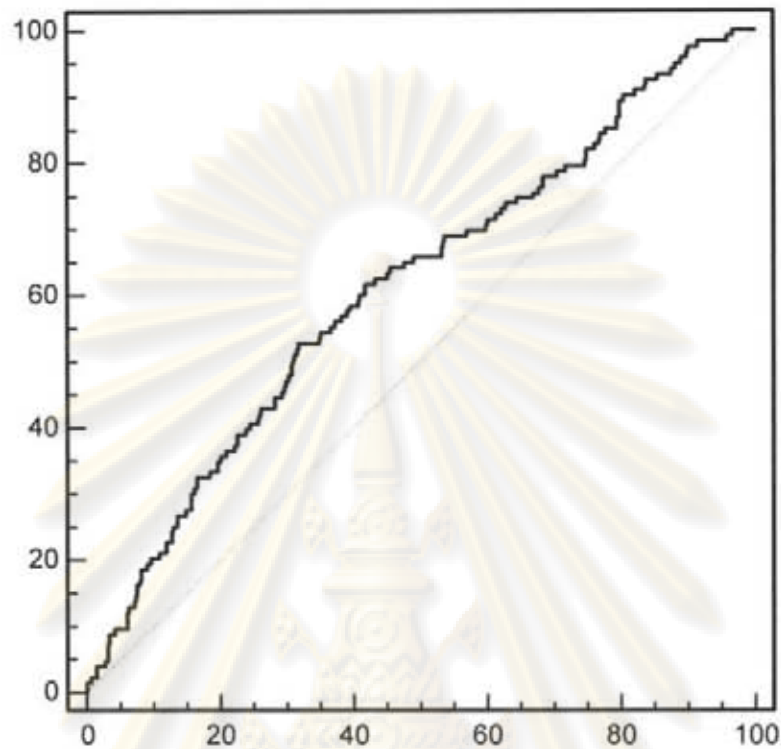


Figure 3 Changes in RNPD around Credit Rating Downgrades



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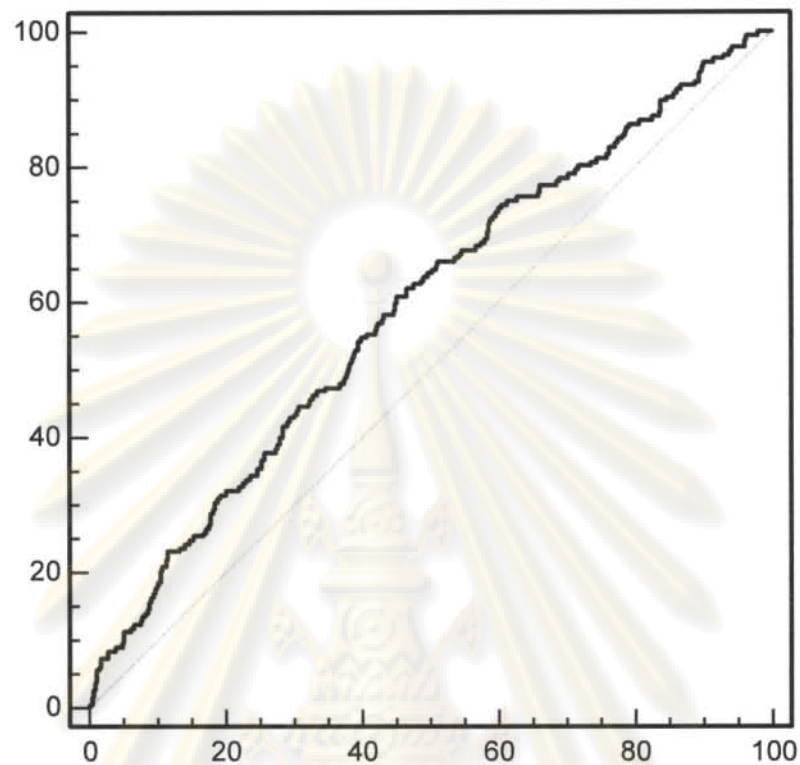
Figure 4 Upgrades Prediction by BQRC Model



Area under the ROC curve (AUC)	0.611
Standard error	0.0279
95% Confidence interval	0.587 to 0.635
z statistic	3.989
Significance level P (Area=0.5)	0.0001

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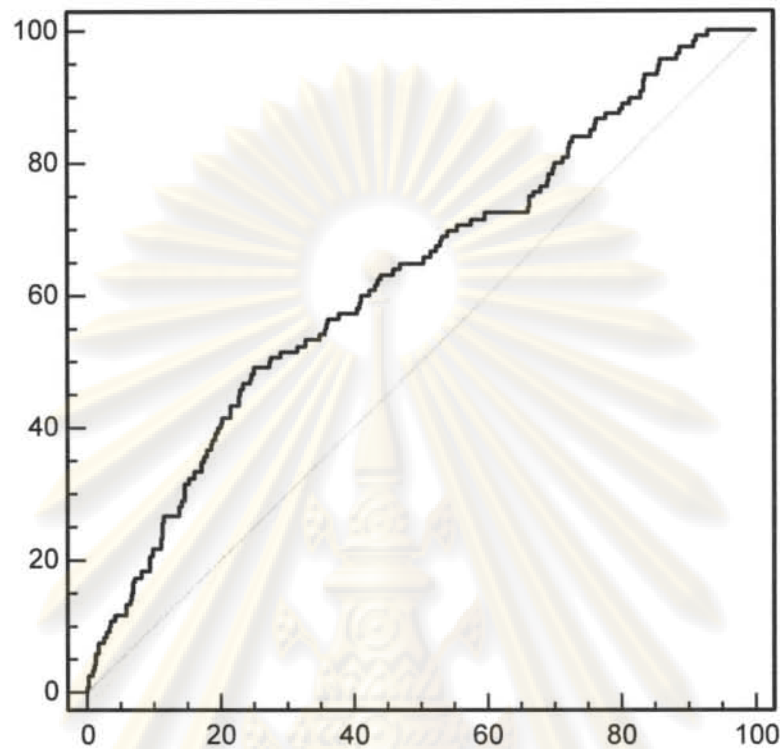
Figure 5 Downgrades Prediction by BQRC Model



Area under the ROC curve (AUC)	0.592
Standard error	0.0214
95% Confidence interval	0.568 to 0.617
z statistic	4.308
Significance level P (Area=0.5)	0.0001

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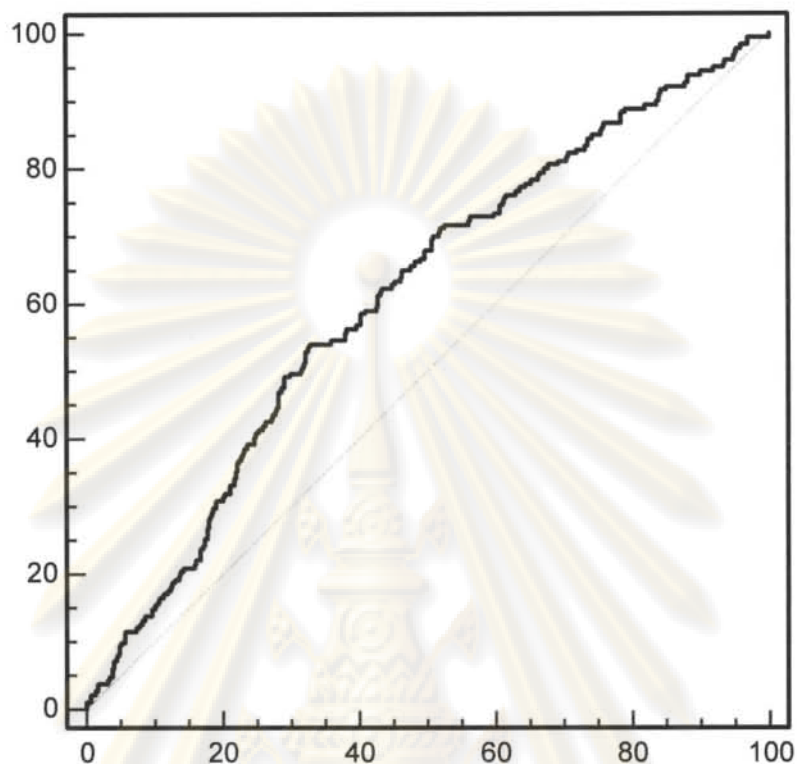
Figure 6 Upgrades Prediction by Adjusted BQRC Model



Area under the ROC curve (AUC)	0.627
Standard error	0.0282
95% Confidence interval	0.603 to 0.651
z statistic	4.516
Significance level P (Area=0.5)	0.0001

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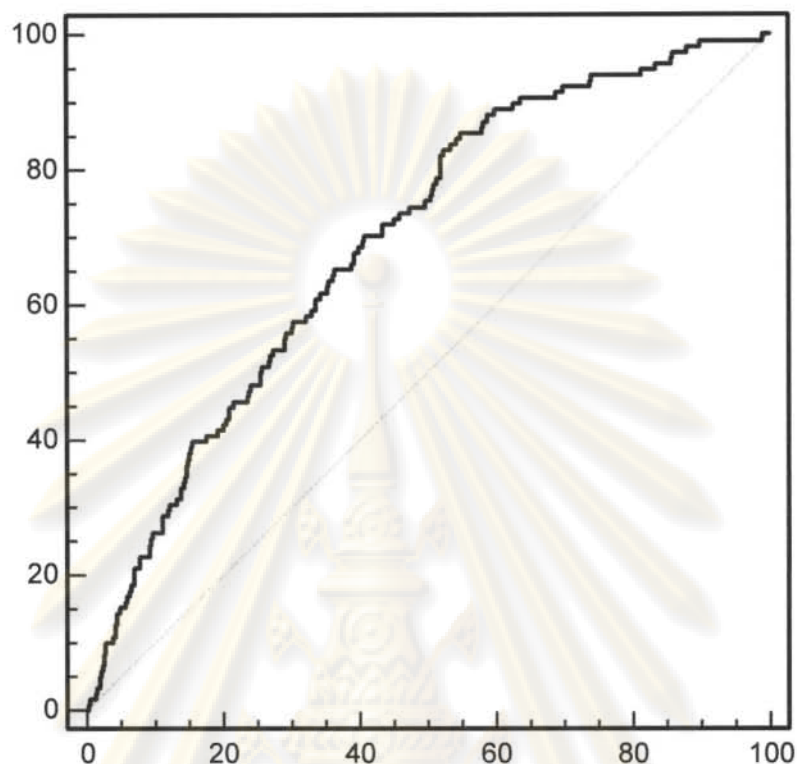
Figure 7 Downgrades Prediction by Adjusted BQRC Model



Area under the ROC curve (AUC)	0.610
Standard error	0.0233
95% Confidence interval	0.586 to 0.634
z statistic	4.719
Significance level P (Area=0.5)	0.0001

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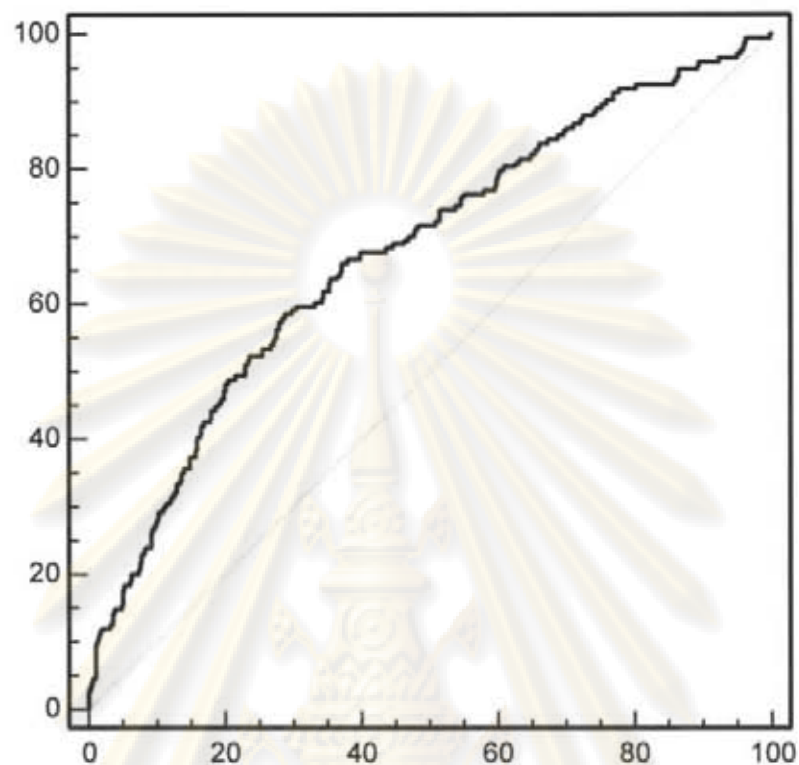
Figure 8 Upgrades Prediction by Adjusted BQRC Model with RNPD



Area under the ROC curve (AUC)	0.695
Standard error	0.0219
95% Confidence interval	0.672 to 0.718
z statistic	8.918
Significance level P (Area=0.5)	0.0001

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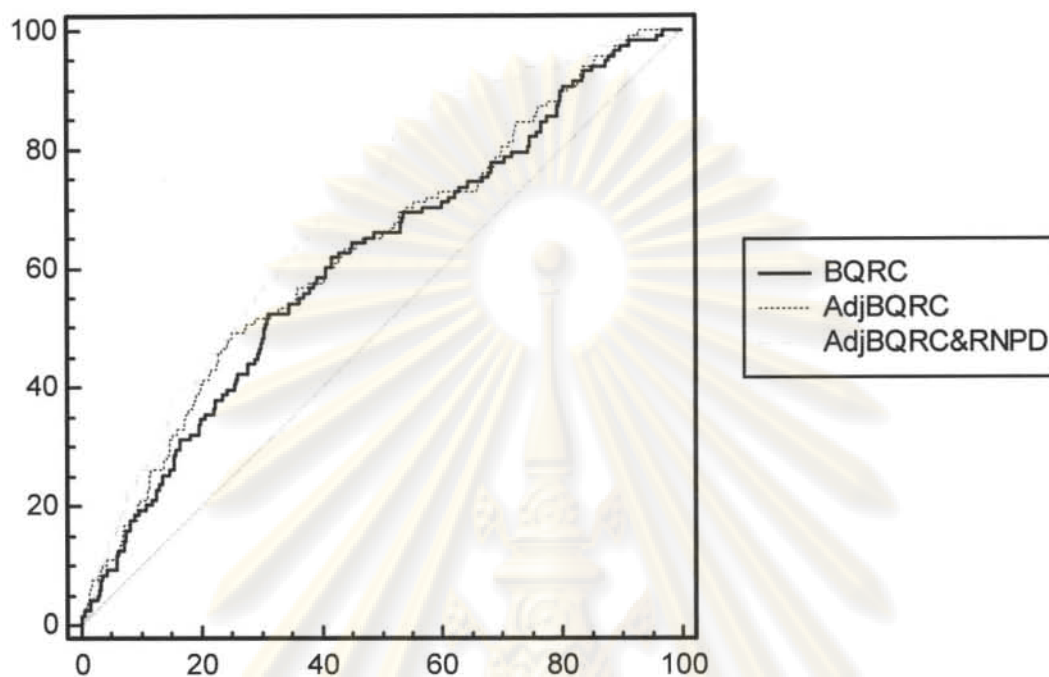
Figure 9 Downgrades Prediction by Adjusted BQRC Model with RNPD



Area under the ROC curve (AUC)	0.676
Standard error	0.0234
95% Confidence interval	0.652 to 0.699
z statistic	7.54
Significance level P (Area=0.5)	0.0001

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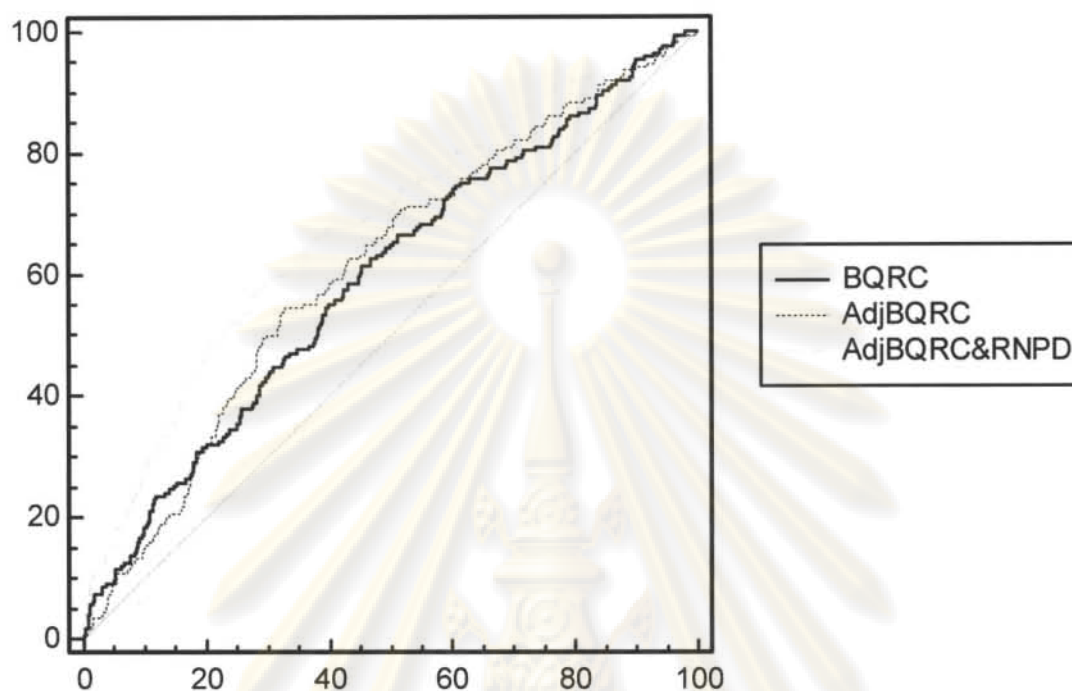
Figure 10 Comparison of ROC Curve - Upgrades Prediction between BQRC, Adjusted BQRC, and Adjusted BQRC with RNP Model



Pairwise comparison of ROC curves

BQRC ~ AdjBQRC	
Difference between areas	0.0185
Standard error	0.0109
95% Confidence interval	-0.0030 to 0.0400
z statistic	1.688
Significance level	P = 0.091
BQRC ~ AdjBQRC&RNP	
Difference between areas	0.0841
Standard error	0.0349
95% Confidence interval	0.0157 to 0.1530
z statistic	2.410
Significance level	P = 0.016
AdjBQRC ~ AdjBQRC&RNP	
Difference between areas	0.0657
Standard error	0.0336
95% Confidence interval	-0.0001 to 0.1310
z statistic	1.957
Significance level	P = 0.050

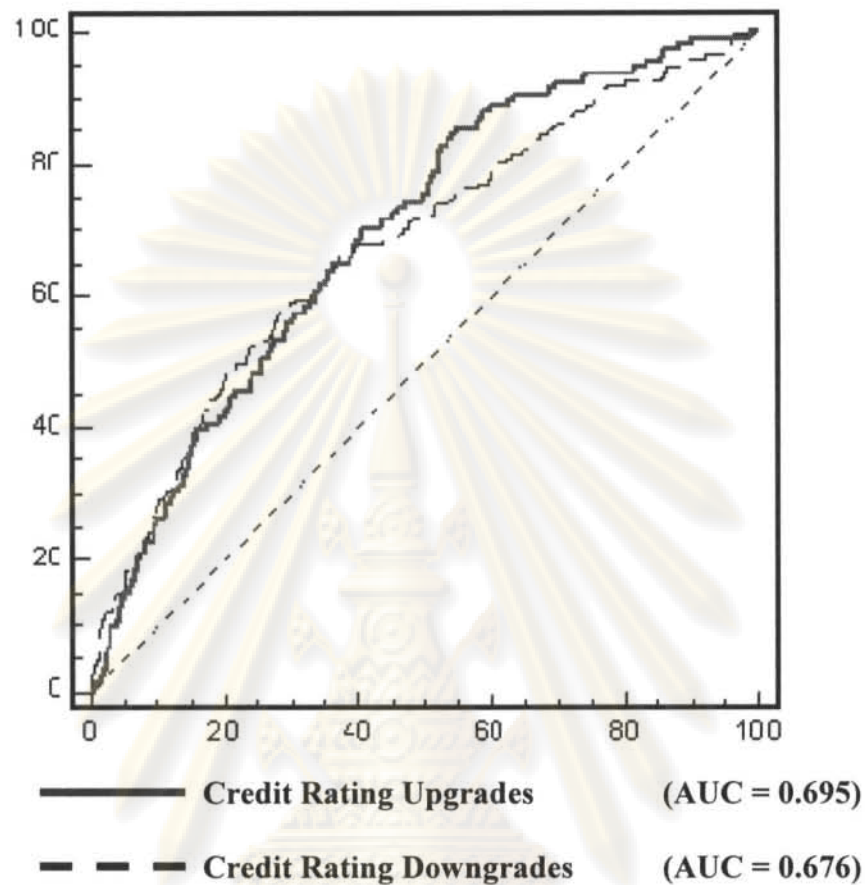
Figure 11 Comparison of ROC Curve - Downgrades Prediction between BQRC, Adjusted BQRC, and Adjusted BQRC with RNP Model



Pairwise comparison of ROC curves

BQRC ~ AdjBQRC	
Difference between areas	0.0170
Standard error	0.0312
95% Confidence interval	-0.0441 to 0.0781
z statistic	0.544
Significance level	P = 0.586
BQRC ~ AdjBQRC&RNP	
Difference between areas	0.0834
Standard error	0.0298
95% Confidence interval	0.0251 to 0.1420
z statistic	2.804
Significance level	P = 0.005
AdjBQRC ~ AdjBQRC&RNP	
Difference between areas	0.0664
Standard error	0.0169
95% Confidence interval	0.0334 to 0.0995
z statistic	3.941
Significance level	P < 0.001

Figure 12 Comparison of ROC Curve - Upgrades and Downgrades Prediction by Adjusted BQRC with RNPD Model

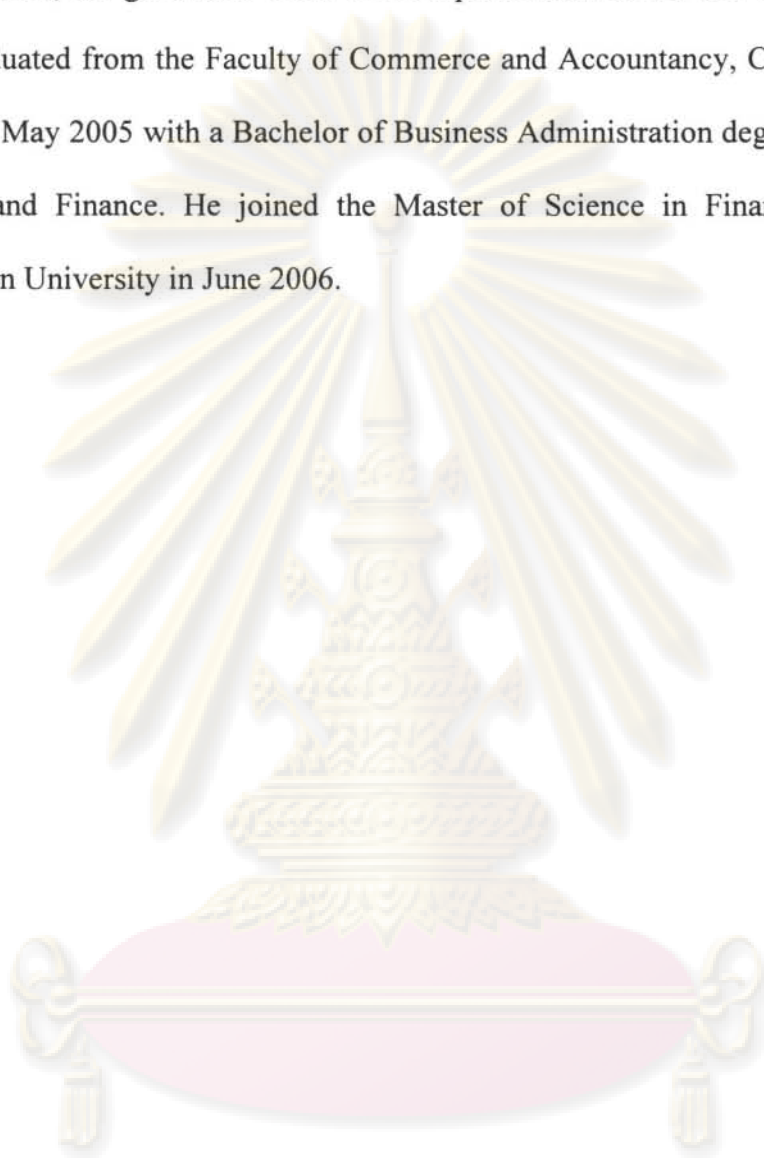


Upgrade ~ Downgrade Prediction by Adjusted BQRC Model with RNPD	
Difference between areas under independent ROC curves	0.0190
Standard error	0.0320
z statistic	0.593
Significance level	P = 0.553

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BIOGRAPHY

Mr. Wittaya Piya-arayanan was born in June 11, 1983 in Bangkok. At the secondary school, he graduated from Taweetapisek School. At the undergraduate level, he graduated from the Faculty of Commerce and Accountancy, Chulalongkorn University in May 2005 with a Bachelor of Business Administration degree, majoring in Banking and Finance. He joined the Master of Science in Finance program, Chulalongkorn University in June 2006.



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