CHAPTER II

Literature Review

The finance literature contains a number of papers that examine rating change and ratings transition. Better understanding the behavior of rating could better benefit the financial institutions and investors. Cantor (2004) indicates several reasons why credit risk managers are concerned about the probabilities of ratings transition. First, many portfolio risk models update value-at-risk numbers on a periodic basis to reflect a change in a portfolio's rating distribution. Second, since defaults are rare events and historical data sets generally do not go back very far in time, researchers study rating transition statistics with the goal of estimating long-term default predictions from short-term credit risk dynamics. Third, rating transition data can be used to understand the rating process and how credit ratings relate to alternative measures of credit risk. This paper summarizes related literatures as follows.

2.1 Rating Determinant

Many papers used financial accounting ratios and other publicly available information to predict credit rating and corporate bankruptcies. Altman (1968) explained corporate bankruptcy status in the US based on accounting and financial variables and developed the Z-score by using multiple discriminant analysis. This approach discriminates between two groups, bankrupt and non-bankrupt firms, by deriving a linear combination of certain pre-determined factors that best discriminates between the two groups. In particular, Altman demonstrated that a linear combination of financial ratios, measures of leverage, sales efficiency, cash flow, and operating capital, performs well in discriminating between firms that went bankrupt in the subsequent year and those that did not. Kaplan and Urwitz (1979) concentrated on statistical techniques for explaining and predicting bond ratings. They found that the statistical models for bond ratings are alive and well. The independent variables include firm size, subordination, market beta and several financial ratios. The results indicate that subordination, total assets, leverage and market beta could predict two thirds of a hold-out sample of newly issued bonds. After developing the model by including additional two financial ratios, it can improve the prediction capability a bit further.

Subsequently, Blume et al. (1998) applied an ordered probit analysis of a panel of firms by using accounting variables and market-driven variables to study credit ratings. Their variables include interest coverage, operating margin, debt leverage, market model beta, and standard error. All of these match expectation except total debt leverage. They concluded that this exception means for a given level of long-term debt leverage, a firm with more short-term debt in its capital structure will tend to receive a higher credit rating. Furthermore, Shumway (2001) forecasted bankruptcy by developing hazard rate model that can resolve the disadvantage of static model, time-varying, and he added equity market variables to the set of accounting measures used in previous literatures. He pointed out that his new hazard rate model outperforms alternative models in out-of-sample forecasts. Campbell et al. (2005) then developed the Shumway's model by using market value of total assets instead of book value of total assets since they found that this variable is more proper than the old one. They also added each firm's log price per share as a variable. This captures a tendency for distressed firms to trade at low prices per share, without reverse-splitting to bring price per share back into a more normal range.

Generally, credit ratings are also depended on other factors such industry, domicile, and business cycle. Belkin, Suchower, and Forest (1998) and Nickell, Perrraudin, and Varotto (2000) show that transition matrices of the ratings depend on the business cycle. Belkin et al. (1998) apply a univariate model whereby all ratings respond to business cycle shifts in the same way while Nickell et al. (2000) propose an ordered, discrete choice model which allows a transition matrix to be conditioned on the industry, the country domicile, and the business cycle. Nevertheless, these studies do not think about the rating category specific variables that have an effect on the individual category e.g. AA, BBB rating transitions. In order to resolve this problem, Wei (2003) develops a multi-factor, Markov chain model which allows transition matrices to be time-varying and driven by rating category specific latent variables. However, the rating category specific latent variables that drive the transition matrix are not actually identified in the paper. Kim et al. (2006) proposed a random effects multinomial regression model to estimate transition probabilities of credit ratings by using accounting ratios and economic factors such as discount rate, unemployment rate, exchange rate, and GDP growth rate. They conclude that the retained earning to total assets is the most influential factor on the migration into higher credit ratings.

2.2 Rating Quality and Stability

Many studies analyze trends in corporate credit ratings by examining the direction of ratings change, stability of ratings, length of time that ratings are held, and default experience of rated issuers. Carty and Fons (1993) used a rating database spanning 70 years from May 1923 through June 1993 to study ratings' qualities. They found that the credit quality of universe of long-term rated issuers remained relatively constant over the period from 1950 through 1979. However, it has deteriorated in each year since then. A marked deterioration in the credit quality of short-term issuers also began at the end of the 1970s but has recently reversed. Also, from the fact that during the period the late 1970s through early 1990s the number of downgrades in corporate bond ratings has exceeded the number of upgrades, leading some to conclude that the credit quality of US corporate debt has declined. However, an alternative reason of this decline in credit quality is that the rating agencies were now using more stringent standards in assigning ratings. Blume et al. (1998) proved this decline by modifying the ordered probit model to provide for the non-linearity in the relationship between ratings and variables such as operating margin, and used panel data to study any changes in rating standards over time. They concluded that rating standards have indeed become more stringent.

However, Cantor and Packer (1995) and Carty (1997) indicated that rating agencies provide a reasonable rating relative to credit risk. Cantor et al. (1997) indicated that the smaller rating agencies, Duff & Phelps Credit Rating Agency (DCR) and Fitch Investors Service, used to assign higher ratings to bond issuers than Moody's and S&P did. Under this circumstance, in order to maintain their competitiveness and popularity in the business, Moody's and S&P might have been forced to adopt softer rating standards to entice their clients. Moreover, Zhou (2001) pointed out that the decline of bond rating were not from business fluctuations and it is not because the agencies' standard but it is because a decline in the real credit quality of corporate bonds. Also, he claimed that the Blume et al. probit model is not misspecified because the probit model has large prediction errors. Moreover, because rating involves a look into the future, credit rating is by nature subjective, and because long-term credit judgments involve so many factors unique to particular industries, issuers, and countries. Therefore, any attempt to reduce credit rating to a formulaic methodology would be misleading and would lead to serious mistakes.

Furthermore, Amato and Furfine (2004) examined the cyclical patterns of rating change. They found that rating agencies keep their ratings usually be stable through credit cycles. However, by the large number of rating downgrades during the 2001-2002 periods and the enhanced role proposed for ratings in bank regulation under Basel II, market participants have expressed concern about the stability of ratings over the credit cycle. Cantor and Mann (2003) verified that credit ratings have been stable over past credit cycles, particularly in comparison to market-based credit measures. Amato and Furfine, nonetheless, go further in indicating that rating change displays very little cyclicality even after controlling for many of the financial and economic determinants of ratings.

Altman and Rijken (2004) argued that the stability of ratings is caused by rating agencies are relatively slow in adjusting their ratings. To prove this statement, they quantify the impact of the long-term default horizon and the prudent migration policy on rating stability from the perspective of an investor by modeling the agency-rating scale with an ordered logit regression model and by modeling the default probability with a logit regression model for various time horizons. They conclude that agencies focus on long-term default rates, and the focus of agencies on long investment horizons explains only part of the relative stability of agency ratings.