Measuring credit risk is always a crucial part in credit risk management process, and as suggested by Fabozzi (2006), quantifying credit risk can be complicated due to the lack of sufficient historical data, the diversity of involved borrowers and the variety in default causes. With the dramatic development of technology, credit risk measurement evolved greatly during the last 20 years. There are three categories of methods for bank credit risk measurement - credit rating, credit scoring and credit modeling.

### 6.1 Fundamentals of Credit Risk Measurement

Generally speaking, measuring credit risk is about trying to obtain some measures of the dispersion of possible future outcomes, and in practice, the focus is usually on the downside outcomes (Lowe 2002). The credit risk in banks should be measured by size as well as scope of the exposure, and as pointed out by Lowe (2002), all kinds of credit risk measuring approaches comprise of four common building blocks, including the probabilities of borrowers defaulting (PDs), the correlation of PDs across borrowers, the possible loss in the event of
6.2 Credit Risk Rating

A credit rating is for assessing the creditworthiness of an individual or corporation to predict the probability of default, which is based on the financial history and current assets and liabilities of the subject. As mentioned by the Federal Reserve (1998), credit risk ratings may reflect not only the likelihood or severity of loss but also the variability of loss over time. For banks, both the internal credit rating and the external one are involved in their credit risk assessment.

6.2.1 Internal Credit Rating

The internal credit ratings of banks, as suggested by Jacobson, Linde and Roszbach (2003), are the summary of the risk properties of the bank loan portfolio. They can be treated as monotonic transforms of the probability of default and shape the nature of credit decisions that banks make daily (Treacy and Carey 1998). A consistent and meaningful internal risk rating system can be a useful means for differentiating the degree of credit risk in loans and other sources of exposure (Basel 1999a). The internal credit ratings of banks are becoming increasingly important since the recommendations, as per...
the latest Basel II accord (Basel 2006), emphasize the adoption of robust internal credit rating system for risk assessment and buffer capital calculation, which will certainly encourage and lead banks to further development in this method.

6.2.2 External Credit Rating

The external credit ratings are provided by credit rating agencies are a measure of the long-term fundamental strength of companies (Gonzalez et al. 2004). One noticeable issue is that credit rating agencies usually take a long-term perspective, which implies a lower sensitivity of their ratings to short-term fluctuations in credit quality, and rating migrations are triggered only by significant credit quality change (Altman and Rijken 2004). Despite of this, those ratings still play a key role in pricing credit risk. Since in the standardized approach to credit risk of Basel II accord (Basel 2006), banks are allowed to slot assets into weighting bands (see Table 6.1) according to ratings from eligible external agencies (Jackson 2001), it is quite possible that the future role of external ratings will keep on expanding.
Credit-scoring approaches, as stated by Reto (2003), can be found in virtually all types of credit analysis and share the same concept with credit ratings. A credit scoring system determines points for each pre-identified factor, which are combined to predict the loss probability and the recovery rate. According to Altman and Saunders (1998), there are two types of accounting based credit-scoring system in banks--univariate and multivariate. The first one can be used to compare various key accounting ratios of potential borrowers with industry or group norms while in the latter one, key accounting variables are combined and weighted for producing a credit risk score or a probability of default measure, which if higher that a benchmark, indicates a rejection to the loan applicant or a further scrutiny.
6.4 Credit Risk Modeling

According to Basel (1999b), credit risk models attempt to aid banks in quantifying, aggregating and managing credit risk across geographical and product lines, and the outputs can be very important to banks' risk management as well as economic capital assignment. Those models, despite of the possible differences in assumptions, share the common purpose to forecast the probability distribution function of losses that may arise from a bank's credit portfolio (Lopez and Saidenberg 1999). And regarding the potential benefits from the application of credit risk models in banking sectors, Basel (1999b) has concluded that they are responsive and informative tools offering banks a framework for examining credit risk in a timely manner, centralizing data on global exposures and analyzing marginal and absolute contributions to risk. According to Jackson, Nickell and Perraudin (1999), four types of models are better known.

6.4.1 Merton-based Models

Merton-based models are also referred to as structural models. The basic principle of this category of models, as suggested by Merton (1974) first, is that a firm is considered to be in default when the value of its assets falls below that of its liabilities. Merton has modeled a firm's asset value as lognormal process, with the equity modeled as a
call option on the underlying assets, and the default is allowed at only a future time \( t \) (Arora, Bohn and Zhu 2005). The current value and the volatility of the firm's assets, the outstanding debt and its maturity are required as inputs, from which the borrower's default probability can be determined (Hull, Nelken and White 2004). Based on the Merton model, Moody's KMV model has been developed for providing a term structure of default risk probabilities. The term "Distance-to-default" is proposed in the KMV model, which is calculated from the market assets value of the firm, the volatility as well as the default point term structure, and the model derives the actual probability of default - the Expected Default Frequency for each obligor instead of relying on the average historical transition frequencies produced by the rating agencies (Crouhy, Galai and Mark 2000).

6.4.2 Rating-based Models

One of the most widely used ratings-base models is the Credit Metrics from JP Morgan. It is a tool for assessing portfolio risk that arises from changes in debt value caused by changes in obligor credit quality, and causes of the changes in debt value include possible default events and upgrades as well as downgrades in credit quality (JP Morgan 1997). According to Jackson, Nickell and Perraudin (1999), the obligor credit quality change probability can be expressed as the probability of a standard normal variable falling
between various critical values that are calculated from the borrower's current credit rating and historical data of credit rating migrations. The measurement framework of Credit Metrics is illustrated in Figure 6.1 below. Credit Metrics suffers from a major problem, as pointed out by Crouhy, Galai and Mark (2000), that this approach relies on transition probabilities based on average historical frequencies of defaults and credit migration, which affects the accuracy of calculations.

Figure 6.1: Credit Metrics framework: The four building blocks (source: JP Morgan 1997)
6.4.3 Actuarial Models

The example of actuarial models is Credit Risk (Figure 6.2 below gives the model framework), which predicts the loan loss distribution with the help of statistical techniques. In the model, borrowers are allocated among country-industry segments and default of individual loans is assumed to follow a Poisson process. The development of a loan is understood as that either the obligor pays the amount due or the loan defaults, and no profits or losses from rating migrations have to be considered. As concluded by Gundlach and Lehrbass (2004), the attractiveness of Credit Risk is that it is more intuitive and better suited to practical needs.

There is no requirement to provide the complete cash flow vector for each loan or to update spread curves for each rating class on regular basis.
Input

• default rates
• default rates/volatilities
• exposures
• recovery rates

Stage 1

Building Block #1
What is the FREQUENCY of defaults?

Stage 2

Building Block #3
Distribution of default losses

Building Block #2
What is the SEVERITY of the losses?

Figure 6.2: Credit Risk: Risk measurement framework (source: Credit Suisse 1997)
6.4.4 Macroeconomic Models

Among macroeconomic models, Credit Portfolio View is most widely used, which is proposed by McKinsey. It is a multi-factor model based on the casual observation that default and migration probabilities are linked to the economy (Crouhy, Galai and Mark 2000). The model measures only default risk, and the times series of default rates per industry sector (Table 6.2 below gives an example) are required as the most important data input for simulating macroeconomics scenarios, which are used for estimating the conditional distribution of default probabilities for individual credits (Kern and Rudolph 2001).

<table>
<thead>
<tr>
<th>Default Rates / Industry-Segment / Germany</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
<th>Year 5 etc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: &quot;Statistisches Bundesamt&quot;, Germany</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture / Forestry / Fishery</td>
<td>p1</td>
<td>0.31%</td>
<td>0.40%</td>
<td>0.56%</td>
<td>0.56%</td>
</tr>
<tr>
<td>Energy / Water Supply / Mining</td>
<td>p2</td>
<td>0.10%</td>
<td>0.05%</td>
<td>0.07%</td>
<td>0.07%</td>
</tr>
<tr>
<td>Manufacturing Industry</td>
<td>p3</td>
<td>0.48%</td>
<td>0.64%</td>
<td>0.86%</td>
<td>0.86%</td>
</tr>
<tr>
<td>Building Industry</td>
<td>p4</td>
<td>0.71%</td>
<td>1.04%</td>
<td>1.45%</td>
<td>1.31%</td>
</tr>
<tr>
<td>Trade</td>
<td>p5</td>
<td>0.30%</td>
<td>0.40%</td>
<td>0.56%</td>
<td>0.56%</td>
</tr>
<tr>
<td>Transportation / Communication</td>
<td>p6</td>
<td>0.41%</td>
<td>0.55%</td>
<td>0.74%</td>
<td>0.73%</td>
</tr>
<tr>
<td>Financial Institutions / Insurance Ind.</td>
<td>p7</td>
<td>0.64%</td>
<td>0.60%</td>
<td>0.71%</td>
<td>0.80%</td>
</tr>
<tr>
<td>Services / Others</td>
<td>p8</td>
<td>0.28%</td>
<td>0.36%</td>
<td>0.48%</td>
<td>0.50%</td>
</tr>
<tr>
<td>All Sectors</td>
<td>p</td>
<td>0.38%</td>
<td>0.50%</td>
<td>0.68%</td>
<td>0.68%</td>
</tr>
</tbody>
</table>

Table 6.2: Credit Portfolio View-data input: country-industry-sectors and the time series of sector-specific default rates (source: Kern and Rudolph 2001)