



T.C.
YEDITEPE UNIVERSITY
GRADUATE INSTITUTE OF SOCIAL SCIENCES

CREDIT RISK AND RISK MANAGEMENT

by

Hicabi ERSOY

**Submitted to the Institute of Social Sciences
In partial fulfillment of the requirements for the degree of
Master of
Business Administration**

ISTANBUL, 2001

ABSTRACT

CREDIT RISK AND RISK MANAGEMENT

HİCABİ ERSOY

The financial risk has increasing impact on the financial institutions over the past two decades. It's developed and implemented a lot of sophisticated models during this period. These models have gained popularity not only among bank managers, but also in amendments to the international bank regulatory framework. One of the most popular source of the financial risk is the credit or default risk. Many developments related with the credit risk are taken place including developments of statistical models, changes of regulatory issues, increasing of data sources.

In the light of these developments, it is important to understand how to control the credit risk so as to gain the competitive advantage and try to minimize the loss due to credit/default risk.

The objective of this thesis is the presenting the ways of how to control and mitigate the credit risk and bring out the latest improvements of the regulatory or legal issues.

Risk and especially credit risk is explained briefly in the introduction of this thesis, the financial risks are explained in the second part, and following the second part, it's explained credit risk, credit risk models and VaR. Finally, in the fourth part detailed information about the credit risk ratings and its impacts on the credit risk management models have been given.

Key Words :Risk, Financial Risks, Credit/Default Risk, Risk Rating.

ÖZET

KREDİ RİSKİ VE RİSK YÖNETİMİ

HİCABİ ERSOY

Son yirmi yıldır finansal risk kuruluşlar üzerinde artan bir şekilde etkili olmuştur. Bu süreçte, bu alanda bir çok yenilik ve gelişmiş model ortaya çıkmış ve bunlar sadece banka yöneticilerini ilgilendirmekle kalmamış, düzenleyicilerin de dikkatini çekmiştir. Finansal risk kaynaklarından son yıllarda çok popüler olanlardan biri de kredi riski veya kredinin geri ödenmeme riskidir. Kredi riskiyle ilgili yeni modeller geliştirilmiş, yasal düzenlemelerde değişiklikler oluşmuş ve veri kaynakları artmıştır.

Bu gelişmelerin ışığında, kredi riskini yönetmek, rekabet üstünlüğü kazanmak ve kayıpları minimize etmek açısından önemlidir.

Bu tezin amacı, kredi riskini kontrol etmek ve yönetmek için gerekli olan yöntemleri ortaya koymak, düzenleyicilerin, bu konudaki, yaptıkları son gelişmeleri sunmaktır.

Tezin giriş bölümünde, genel olarak risk ve kredi riski kısaca anlatılmış, ikinci bölümde, başlıca risk tanımları ve finansal riskler açıklanmış, kredi riski, kredi riski modelini oluşturan unsurlar ve VaR konuları ile bunlara ilişkin istatistik modellere üçüncü bölümde değinilmiştir. Dördüncü ve son bölümde ise risk derecelendirmesi anlatılmıştır.

Anahtar Kelimeler :Risk, Finansal Riskler, Kredi(Borç Ödememe) Riski, Kredi Riski Derecelendirmesi.

1. INTRODUCTION

The issue is how to price and control potential losses from default(Jorion, 1997). Credit risk, one of the building blocks of the theory of particle finance, arises when counterparties are unwilling or unable to fulfill their contractual obligations. It encompasses both default risk and market risk. Default risk is the objective assessment of the likelihood that a counterparty will default; market risk measures the financial loss that will be experienced should the client default. In other words the economic value of a credit instrument may decline even if a counterparty does not default(see section 3.6.2.6. Default Mode Paradigm and Mark to Market Paradigm).

Credit risk in derivatives has two distinguishing characteristics. The first is the need to quantify exposure, or market risk. In traditional banking, the credit exposure is easily determined; for a bond or loan contract, it is measured as the outstanding principal plus any accrued interest. With derivatives, the exposure depends on whether the contract has positive or negative market value and on the future changes in contract values.

The second characteristic is the potential for diversification across counterparties and portfolios of instruments. As exposures tend to offset each other, the risk of the portfolio will be considerably less than the sum of each credit exposure. Institutions that can accurately quantify the credit risk of their portfolio will be able to price their products better thereby gaining an advantage over the competition.

The theory of credit risk is relatively less developed than VAR-based models of market risk. Credit risk is also under intense research effort in both industry and academia. As a result, we should expect this area to evolve rapidly.

Over the past two decades, financial risk has increasing impact on the financial institutions. Resultingly many institutions have devoted many resources to developing internal risk models for better quantifying the financial risks. During this period, they have developed and implemented a variety of sophisticated models. These models have gained popularity not only among senior bank managers but also in amendments to the international bank regulatory framework.

The first purpose of the models is quantifying the risk. Risk management is the process by which various risk exposures are identified, measured and controlled. Understanding the risk means that financial managers can consciously plan for the consequences of adverse outcomes. By doing so, they will be better prepared for the inevitable uncertainty. Since the risk means the chance or likelihood that an outcome

other than expected will occur, primary duty of the financial institution's manager is to protect his institution from the danger of losses.

Financial risks can be classified into the market risk, credit risk, liquidity risk, operational risk, and legal risk. Among these, more general sense, credit risk(also can be called default risk) can be defined as the probability that a borrower will default on a commitment to repay debt or loan.

In recent years, risks inherent in the operations of financial institutions have become much more diversified and complicated. In this environment, credit risk management is a prominent or striking issue given the degree of impact it will have on a financial institution's management and operations.

The banking industry has undergone significant change over the past ten years. The development of capital markets and easy access to information has created a significant challenge for banking industry.

More and more financial transactions can be performed outside the banking sector, resulting in their increasing disintermediation. Additionally, the continuous evolution of traded instruments now allows the industry to hedge or alter the risk in almost any position. These developments have changed the risk profile of banks, shifting bank management's focus away from simple asset liability and credit related risks, to today's environment, where the bank management must deal with a broad array of risks as well as manage information(Global Association of Risk Professionals-GARP- the Committee on Regulation and Supervision, 1999).

Credit risk is traditionally the main risk of banks. Banks are in the business of taking credit risk in exchange for a certain return above riskless rate. Banks above all other institutions, including corporations, insurance companies and asset managers, face the greatest challenge in managing their credit risk. One of the credit risk managers' tools is the credit risk management model.

In the past, risk managers relied heavily on their intuitive feelings when making decisions on credit risk. Obviously, credit risk can be managed by more strict enforcement of traditional credit processes such as tight underwriting standards, setting up limits, counterparty monitoring. However, risk managers are increasingly seeking to quantify and integrate the overall credit risk assesment within a measure, which captures to market, rating change and default risks(Guption et al., 1997).

A credit risk management model tells the credit risk manager how to allocate scarce credit risk capital to various businesses so as to optimize the risk and return characteristics of the firm (Skora, 1998).

It is clear that a credit risk management model will not replace the quality of the decisions that the experienced credit risk manager will make, but it will focus minds on the marginal credit risk that a bank is exposed to (Cormac, 1999). Credit risk management, briefly, is the process by which the exposure is defined, calculated, and resulted in required action.

Credit risk models are dynamic and can process a large number of transactions in a short period of time and can be tailored to capture the unique risks inherent in each product or sub-portfolio. Additionally, they can factor in the benefits of diversification and the other risks associated with the credit products.

As financial institutions continue to expand across geographic boundaries and as the nature of loan and investment products become increasingly more complex, bank management have to look beyond the traditional transaction-by-transaction approach of managing credit risk if they are to manage in a consistent, timely, and prudent fashion. Similarly, as hybrid products such as credit derivatives gain further acceptance, the line between the different risk elements are less clear, creating an increased need for credit risk models to better manage these risks.

2. THE RISK AND NEED FOR RISK MANAGEMENT

Corporations are in the business of managing risks. The most adept ones succeed, others fail. Whereas some firms passively accept financial risks, others attempt to create a competitive advantage by judicious exposure to financial risks. In both cases, however, these risks should be carefully monitored because of their potential for damage(Jorion, 1997).

2.1. What is Risk?

Risk can be defined as the volatility of unexpected outcomes, generally the value of assets or liabilities of interest. Corporations are exposed to three types of risks:

- Business,
- Strategic, and
- Financial risks.

Business risks are those that the corporation willingly assumes to create a competitive advantage and add value for shareholders. Business, or operating risk pertains to the product market in which a firm operates, and includes technological innovations, product design, and marketing. Operating leverage, involving the degree of fixed versus variable costs, is also largely a choice variable. Judicious exposure to business risk is a “core competency” of all business activity.

In contrast, the strategic risks are those resulting from fundamental shifts in the economy or political environment. These risks are difficult to hedge, except by diversifying across business lines and countries.

Financial risks are related to possible losses in financial markets. Movements in financial variables such as interest rates and exchange rates create risks for most corporations. Exposure to financial risks can be carefully optimized so that firms can concentrate on what they do best manage exposure to business risks. In contrast to industrial corporations, the primary function of financial institutions is to manage financial risk actively; banks now realize that they must precisely measure sources of risks as prelude to controlling and properly pricing risks. Understanding risk means that financial managers can consciously plan for the consequences of adverse outcomes and, by so doing, be better prepared for the inevitable uncertainty; thus they can offer better prices for managing risks than the competition. Risk management is the process by which various

risk exposures are identified, measured, and controlled. In sum, financial risk management has become a tool essential to the survival of all business activity.

The most important reason for the growth of the risk management industry is the volatility of financial variables.

- The fixed exchange rate system broke down in 1971, leading to flexible and volatile exchange rates.
- The oil price shocks, starting in 1973, were accompanied by high inflation and wild swings in interest rates.
- On Black Monday, October 19, 1987, U.S. stocks collapsed by 23 percent, wiping out \$ 1 trillion in capital.
- The drive toward economic and monetary unification in Europe was stalled by the blow-up in the European Monetary System in September 1992.
- In the bond debacle of 1994, the Federal Reserve Bank, after having kept interest rates low for three years, started a series of six consecutive interest rate hikes that erased \$ 1.5 trillion in global capital.
- Japanese stock prices fell, with the nikkei index *sliding* from 39,000 at the end of 1989 to 17,000 three years later. A total of \$ 2.7 trillion in capital was lost, leading to an unprecedented financial crisis in Japan(Jorion, 1997).

The only constant across all these events is their unpredictability. Each time, market observers were aghast at a rapidly of these changes. These events have had profound effects on financial markets and on corporations, global and domestic alike. Financial Risk management provides a partial protection against such sources of risk.

It is difficult to understand financial risks without a good grasp of the links between *interest rates, exchange rates, commodity prices, and stock markets*. Before the 1970s, banks were either heavily regulated or comfortably cartelized in most industrial countries. Regulations such as ceilings on interest rate deposits effectively insulated bankers from movements in interest rates. Industrial corporations, selling mainly in domestic markets, were not too concerned about exchange rates. Deregulation forced financial institutions to pay more attention to the financial markets. Increased trade forced firms to recognize the truly global nature of competition. As a result, corporations cannot afford to ignore financial risks.

2.2. Types of Financial Risks

Generally financial risks are classified into the broad categories of

- market risks,
 - interest rate risk,
 - exchange rate risk,
 - equity risk,
- credit risks,
- liquidity risks,
- operational risks,
- legal risks.

2.2.1. Market Risks

"**General market risk**" is the risk of loss arising from changes/movements in value of positions in the trading book due to changes in equity prices, interest rates and foreign currency exchange rates. Positions are made up of:

- a) interest rate related debt securities,
- b) equities,
- c) other securities,
- d) derivative contracts based on the instruments referred to above,
- e) all asset and liability items denominated in different currencies which are

included in the on and off balance sheet.

The components of market risk are "interest rate risk", "equity position risk" and "foreign exchange risk"

Market risks arise from changes in the prices of financial assets and liabilities (or volatilities) and are measured by changes in the value of open positions or in earnings.

Market risks include basis risk, which occurs when relationships between products used to hedge each other change or break down, and gamma risk, due to nonlinear relationships. Holders of large positions in derivatives have been hurt by basis and gamma risk, even though they thought they were fully hedged (Jorion, 1997).

Market risk can take two forms:

- **Absolute Risk:** Measured by the loss potential in dollar terms, and
- **Relative Risk:** Relative to a benchmark index.

While the former focuses on the volatility of total returns, the latter measures risk in terms of tracking error, or deviation from the index. In addition to linear measures of risk, VAR can also capture basis risk, gamma risk, and can be extended easily to relative risk(Jorion, 1997).

The primary purpose of VAR systems is to quantify market risk. Ideally, such systems should be structured to enable management to take prompt remedial action in case of losses or unusual exposures.

Market risk is usually defined as the risk to loss in a financial instrument from an adverse movement in market prices or rates. If you own a bond, then a rise in interest rates is adverse, but if you have lent/sold a bond, it is a fall in rates that is adverse. Generally people classify sources of market risk into four categories, *interest rates, equities, foreign exchange and commodities*.

2.2.1.1. Interest rate risk

"**Interest rate risk**" is the probability of loss due to changes in interest rates depending on the bank's position.

2.2.1.2. Exchange rate risk

"**Foreign exchange risk**" is the risk of loss, which may arise from changes in values of foreign currency denominated assets and liabilities, against Turkish Lira.

2.2.1.3. Equity risk

"**Equity position risk**" is the probability of loss due to changes in equity prices depending on the bank's position in equities (Regulation on Measurement and Assessment of Capital Adequacy of Banks, Issued by the Banking Regulation and Supervision Board, *Published in the first supplementary issue of the Official Gazette no. 24314 of 10.02.2001*).

2.2.2. Credit Risk

Credit risk arises when counterparties are unwilling or unable to fulfill their contractual obligations. Its effect is measured by the cost of replacing cash flows if the other party defaults. More generally, credit risk can also lead to losses when debtors are downgraded by credit agencies, usually leading to a fall in the market value of their obligations.

Potential losses on derivatives if counterparties default are much lower than notional amounts(face value). Instead, the loss is the change in the value of position, if

positive when a default occurs. In contrast, corporate bonds and bank loans are exposed to the loss of the whole face value. In case of default, hapless investors can receive only cent on the dollar, some times after years of litigation.

Credit risk also includes sovereign risk. This occurs, for instance, when countries impose foreign exchange controls that make it impossible for counterparties to honour their obligations. Whereas default risk is generally company specific, sovereign risk is country specific.

Credit risk takes the form of presettlement risk, and settlement risk. The latter refers to the possibility that a counterparty might default on a contract after one party has already made payment. This possibility is very real for foreign exchange transactions, where payments may be made in the morning in Europe against delivery in America later. Indeed When Herstatt Bank were bankrupt in 1974, it had received payments from a number of counterparties but defaulted before payments were made on the other legs of the transaction, thus potentially destabilizing the global banking system. This bank failure was the impetus for the creation of the Basle Committee, which 20 years later promulgated capital adequacy requirements(Jorion, 1997).

Managing credit risk has both qualitative and quantitative aspects. Determining the creditworthiness of a counterparty is the qualitative component. Recent advances have led to quantitative assesment of credit risk(Jorion, 1997).

2.2.3. Liquidity Risk

Liquidity Risk takes two forms:

- Market/Product Liquidity and
- Cash flow/Funding.

The first type of risk arises when a transaction cannot be conducted at prevailing market prices due to insufficient market activity. It is especially a problem for illiquid OTC(Over the Counter) contracts and when dynamic hedging is used. Liquidity risk, however, can be difficult to quantify and can vary across market conditions. Market/Product liquidity risk can be managed by setting limits on certain markets or products and by means of diversification. Although liquidity risk cannot be formally included in VAR measures, orderly liquidation periods are quite relevant to the choise of the horizon for VAR measures.

The second type of risk refers to the inability to meet cash flow obligations, which may force early liquidation, thus transforming “paper” losses into realized losses. Funding risk can be controlled by proper planning of cash flow needs, which can be controlled by setting limits on cash flow gaps and diversification, as in the previous case.

Liquidity is also related to the holding horizon of the investor. Market conditions may prevent the immediate liquidation of an investment, say a collateralized mortgage obligation(CMO). Illiquidity translates into prices that are temporarily low to CMO. If the condition is temporary, the investor could wait until market prices recover to levels close to the theoretical, or model prices. In such a situation, illiquidity is a minor nuisance. However, for investors in a hurry, such as those who must sell because of the need raise cash for collateral call payments, illiquidity can be fatal.

2.2.4. Operational Risk

Operational risk refer to potential losses resulting from inadequate systems, management failure, faulty controls, fraud, or human error. This includes execution risk, which encompasses situation where trades fail to be executed, sometimes leading to costly delays or penalties, or more generally, any problem in back-office operations, which deal with the recording of transactions and reconciliation of individual trades with the firm’s aggregate position.

Operational risk also includes fraud, situations where traders intentionally falsify information, and technology risk, which refers to the need to protect systems from unauthorized access and tampering. Other examples are systems failures, losses due to natural disasters, or accidents involving key individuals. The best protection against operational risks consists of redundancies of systems, clear separation of responsibilities with strong internal controls, and regular contingency planning.

2.2.5. Legal Risk

Legal risk arise when a counterparty does not have the legal or regulatory authority to engage in a transaction. It can take the form of shareholder lawsuit against corporations that suffer large losses.

Legal risk also include compliance and regulatory risks, which concern activities that might breach government regulations, such as market manipulation, insider trading, suitability restrictions. The regulatory framework, however, varies widely across countries

and, even within a country, may be subject to changes and differences of interpretation. Imperfect understanding of regulations can lead to penalties. Regulatory risk manifests itself in enforcement actions, interpretation.

Risk Management and Two Major Approaches for Managing Risks

The volatility in the financial markets has created financial engineering, as a new field of finance. It aims at providing creative ways to protect against, or speculate on, financial risks. Table 2.1. illustrates the expansion of risk management tools since the early 1970s.

These derivatives provide a mechanism through which institutions can efficiently hedge themselves against financial risks. Hedging financial risks is similar to purchasing insurance; it provides insurance against the adverse effect of variables over which businesses or countries have no control. The other side of hedging is that some of their counterparties might be speculators, who provide liquidity to the market in the hope of making profits on their transactions. Thus, risk has begotten derivatives.

Table 2.1 The Evolution of Risk Management Tools

1972	Foreign Currency Futures
1973	Equity Options
1975	T-Bond Futures
1981	Currency Swaps
1982	Interest Rate Swaps; T-Note Futures; Eurodollar Futures; Equity Index Futures; Options on T-Bond Futures; Exchange –listed Currency Options
1983	Options on Equity Index; Options on T-Note Futures; Options on Currency Futures; Options on Equity Index Futures; Interest Rate Caps and Floors
1985	Eurodollar Options; Swaptions
1987	OTC Compound Options; OTC Average Options
1989	Futures on Interest Rate Swaps; Quanto Options
1990	Equity Index Swaps
1991	Differential Swaps
1993	Captions; Exchange-listed FLEX options
1994	Credit Default Options

(Jorion, 1997)

2.3.1. VAR

Today, banks, many brokerage firms, and mutual funds use some methods to gauge their market exposure. Regulators can force implementation of this system, since they can set capital adequacy requirement based on banks' VAR. In the United States, rating agencies, such as Moody's and Standard and Poor's, the Financial Accounting Standards Board, and the Securities and Exchange Commission have all announced their support for VAR. What is VAR?

VAR summarizes the expected maximum loss (or worst loss) over a target horizon within a given confidence interval (Jorion, 1997).

VAR combines the exposure to a risk with the probability of an adverse market movement.

The VAR approach, however, is more general, because it allows investors to include many assets such as foreign currencies, commodities, and equities, which are exposed to other sources of risk than interest rate movements. Thus, VAR is a giant step forward from conventional risk measures such as maturity, duration, or gap analysis.

VAR is no panacea, however. VAR measures are useful only insofar as users grasp their limitations. VAR is only an educated estimate of market risk. This does not lessen its value any more than other estimates do in other areas of science. Engineering is sometimes defined as "the art of approximation." The same definition can be applied to risk management systems.

VAR is actually a piece of information about the distribution of possible future losses on a portfolio. The actual gain or loss won't be known until it happens. Until then it's uncertain; a random variable. Information about the behaviour of a random variable is called a statistic. As you may guess, there are many statistics about a portfolio's returns, for example the expected return. The VAR is a very useful statistic for risk managers, but it's unlikely that it's the only statistic that has some usefulness. Nevertheless, it is the statistic focused on almost exclusively. Now for the tricky stuff: VAR itself is a random variable, because not only is the portfolio's future return unknown, but the distribution of the portfolio's return must be guessed at by inference from observable data.

That means the calculated VAR is really itself just an estimate of the true VAR. So you could estimate a VAR of the distribution of the VAR. Most people are content with estimating confidence intervals for any estimated parameter, because the confidence interval tells you how precise is your estimate(<http://www.gloriamundi.org/var/FAQ.html>).

Finally, VAR should be viewed as a necessary but not sufficient procedure for controlling risk. It must be supplemented by limits and controls, in addition to an independent risk management function. If the widespread use of VAR leads to an increased focus on sound risk management practices, an important objective will have been met. As a market observer put it, VAR's ultimate reward lies in advancing the risk debate about derivatives down a more constructive path.

2.3.1.1. Assume of VaR as a risk measure

Just about every VaR model assumes that the portfolio under consideration doesn't change over the forecast horizon. This is a fiction, especially for trading portfolios, but trying to incorporate forecasts of position changes into a model forecasting returns is very complicated. VaR models also assume that the historical data used to construct the VaR estimate contains information useful in forecasting the loss distribution. Some VaR models go further and assume that the historical data themselves follow a specific distribution (e.g., a "normal distribution" in RiskMetrics).

Originally VaR was used as an information tool. I.e., it was used to communicate to management a feeling for the exposure to changes in market prices. Then market risk was incorporated into the actual risk control structure. I.e., trading limits were based on VaR calculations. Now it is commonly used in the incentive structure as well. I.e., VaR is a component determining risk-adjusted performance and compensation. Interestingly, the theory of VaR has not kept pace.

While we understand it's usefulness as an information tool, it's not clear how it fits into the "shareholder wealth maximization" paradigm of modern financial theory.

2.3.1.2. Calculation of VaR

It depends on the method used, variance/covariance, Monte Carlo, historical simulation. Generally, it involves using historical data on market prices and rates, the current portfolio positions, and models (e.g, option models, bond models) for pricing those positions. These inputs are then combined in different ways, depending on the method, to derive an estimate of a particular percentile of the loss distribution, typically the 99th percentile loss.

2.3.1.2.1. Monte Carlo

A small principality in Europe. But you knew that. It is a simulation technique. First make some assumptions about the distribution of changes in market prices and rates (for example, by assuming they are normally distributed), then collecting data to estimate the parameters of the distribution). The Monte Carlo then uses those assumptions to give successive sets of possible future realizations of changes in those rates. For each set, the portfolio is revalued. When done, you've got a set of portfolio revaluations corresponding to the set of possible realizations of rates. From that distribution you take the 99th percentile loss as the VaR.

2.3.1.2.2. Historical Simulation

Like Monte Carlo, it is a simulation technique, but it skips the step of making assumptions about the distribution of changes in market prices and rates (usually). Instead, it assumes that whatever the realizations of those changes in prices and rates were in the past is what they can be over the forecast horizon. It takes those actual changes, applies them to the current set of rates, then uses those to revalue the portfolio. When done, you've got a set of portfolio revaluations corresponding to the set of possible realizations of rates. From that distribution you take the 99th percentile loss as the VaR.

2.3.1.2.3. Variance/Covariance Matrix or Parametric method

This is a very simplified and speedy approach to VaR computation. It is so, because it assumes a particular distribution for both the changes in market prices and rates and the changes in portfolio value. Usually, this is the "normal" distribution. The neat thing about the normal is that a lot is known about it, including how to readily obtain an estimate of any percentile once you know the variances and covariances of all changes in position values. These are normally estimated directly from historical data. In this method the VaR

of the portfolio, is a simple transformation of the estimated variance/covariance matrix. So simple that it doesn't really work well for nonlinear positions.

RiskMetrics is a particular implementation of the Variance/Covariance approach to calculating VaR. It is particular, not general, because it assumes a particular structure for the evolution of market prices and rates through time, and because it translates all portfolio positions into their component cash flows (or "equivalent") and performs the VaR computation on those. It is really responsible for popularizing VaR, and is a perfectly reasonable approach, especially for portfolios without a lot of nonlinearity.

A linear risk is one where the change in the value of a position in response to a change in a market price or rate is a constant proportion of the change in the price or rate. Everything that's not linear. For example, options are thought of as nonlinear exposures, because they respond differently to changes in the value of the underlying instrument depending on whether they are in-the-money, at-the-money, or out-of-the-money.

2.3.1.3. Stress Testing / Backtesting

Stress testing as a measure of risk exposure that's complementary to VaR. Stress testing is a measure of potential loss as a result of a plausible event in an abnormal market environment. Two types of stress testing are popular. The first is based on economic scenarios. Pretend your portfolio experiences the 1987 or 1997 stock market crash again. The second is "matrix" based. Change a bunch of assumptions about correlations and variances and see what happens. Neither is statistical in nature, in contrast to VaR. That is, you don't know the probability of any particular scenario.

Backtesting is a statistical process for validating the accuracy of a VaR model. Banking regulators require backtesting for banks that use VaR for regulatory capital. It involves a comparison between the number of times the VaR model under-predicts the subsequent day's loss, versus the number of times such an under-prediction is expected. If losses exceeding VaR have a 1 in 100 chance of occurring, then we expect to see 2 or 3 of those in a year. There is a lot of debate about whether backtesting is meaningful, because it is difficult to validate a model based on a few extreme events - not enough data.

2.3.1.4. Confidence level

The underlying question really is, what percentile of the return distribution gives better information about risk exposure? If the portfolio return distribution were normally distributed, it wouldn't matter, because every percentile is expressible as a constant times the standard deviation of the return, the standard deviation being the only real information you need for risk assessment in the normal distribution case. The trade-off between choice of percentiles in the real world in which we live is really about accuracy. It is more difficult to accurately estimate a point farther out in the tail of the distribution of returns, because there is less observable data to use in the estimation.

Accuracy is in the eye of the beholder. But, which confidence level (99% or 95%) should be used? A general answer to this question is not possible, because it will depend on the nature of the portfolio and the data used in the estimation of VaR. Several studies comparing methodologies were conducted a few years back, typically with linear portfolios, either equities or fx. These tended to show that the variance-covariance approach was better when short histories of market prices were used, because Monte Carlo and Historical Simulation would under estimate the 99th percentile. But It does not recommended generalizing from these studies, because of their limited scope. Because of this, it is very important to have an estimate of precision for every VaR estimate (A confidence interval).

However, you may wish to look farther out in the tail if you believe that your portfolio return distribution is more "fat-tailed" (you may think of it as when the ratio: 99 percentile/95 percentile is greater than if the ratio were calculated for a normally distributed return distribution). If there's more going on out there in the tail, you may want to focus on it more. However, simply because 99th percentile VaR yields a bigger VaR does not mean that using a 99th percentile rather than a 95th percentile VaR is a more conservative of a measure of risk. All it means is that you are looking at a point farther out in the tail and calling that your risk exposure. Whether you use 95 or 99, you are generating an estimate of risk from the same distribution of returns.

2.3.1.5. Time horizon

The standard time horizon (that period over which the VaR forecast is made) is one day for most financial businesses with active trading portfolios. The logic for this horizon is that it would take less than one day to either exit or hedge out all the market risk in any position, so that's really how long is the exposure. This reasoning suggests that the horizon should be tuned to the interval to close out the market exposure. This is a bit simplified, because it ignores liquidity issues (large positions may take longer to exit, simply because they are large), differences among portfolio instruments (it is not reasonable to employ a one day horizon for some positions and a multi-day horizon for others, and then to aggregate them for portfolio VaR calculations), and consistency with credit VaR calculations (typically using a much longer horizon, thereby making aggregation complicated - ignoring all the other theoretical issues in aggregating credit and market risk). These two problems have no completely satisfactory solutions.

So, it may be best to identify a singly horizon that best fits the portfolio's characteristics and use that for everything when calculating VaR(<http://www.gloriamundi.org/var/FAQ.html>).

2.3.2. Capital Asset Pricing Model (CAPM) and Systematic/ Specific Risk

2.3.2.1. Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) was first introduced by William Sharpe in 1964. It extended [Modern Portfolio Theory](#) to introduce the notions of [systematic](#) and specific risk.

CAPM considers a simplified world where:

- There are no taxes or transaction costs.
- All investors have identical investment horizons.
- All investors have identical perceptions regarding the expected returns, volatilities and correlations of available risky investments.

In such a simple world, Tobin's super-efficient portfolio (see [Capital Market Line](#)) must be the [market portfolio](#). All investors will hold the market portfolio, [leveraging](#) or [deleveraging](#) it with positions in the [risk-free asset](#).

CAPM divides the risk of holding risky assets into systematic and specific risk. Systematic risk is the risk of holding the market portfolio. As the market moves, each individual asset is more or less affected. To the extent that any asset is affected by such general market moves, that asset entails systematic risk. Specific risk is the risk which is unique to an individual asset. It represents the component of an asset's volatility which is [uncorrelated](#) with general market moves.

According to CAPM, the marketplace compensates investors for taking systematic risk, but not for taking specific risk. This is because specific risk can be diversified away. When an investor holds the market portfolio, each individual asset in that portfolio entails specific risk, but through diversification, the investor's net exposure is just the systematic risk of the market portfolio.

Systematic risk can be measured using [beta](#). The expected excess return of a portfolio above the risk-free rate is just the portfolio's beta multiplied by the expected excess return of the market portfolio.

2.3.2.2. Beta

Beta measures the **systematic risk** of an equity portfolio. It describes the **sensitivity** of the portfolio to broad market movements. The stock market is assigned a beta of 1.0. By comparison, a portfolio which has a beta of 0.5 will tend to participate in broad market moves, but only half as much as the market overall. A portfolio with a beta of 2.0 will tend to benefit or suffer from broad market moves twice as much as the market overall.

It is possible to construct negative beta portfolios. For example, this can be done by:

- Holding stocks that tend to move against the market,
- **Shorting** stocks, or
- Through **derivative** strategies.

Beta is sometimes used as a measure of a portfolio's risk. This, however, can be misleading because beta does not capture specific risk. Because of specific risk, a portfolio can have a low beta, but still be highly volatile. Its price fluctuations would simply have a low **correlation** with those of the overall market.

2.3.2.3. Modern Portfolio Theory (MPT)

Modern Portfolio Theory (MPT) was introduced by Harry Markowitz with his paper "Portfolio Selection" which appeared in the 1952 Journal of Finance. Thirty-eight years later, he shared a Nobel Prize with Merton Miller and William Sharpe for what has become a broad theory for portfolio selection and corporate finance.

Modern Portfolio Theory explores how risk averse investors construct portfolios in order to optimize **market risk** against **expected returns**. The theory quantifies the benefits of **diversification**. Out of a universe of risky assets, an **efficient frontier** of optimal portfolios can be constructed. Each portfolio on the efficient frontier offers the maximum possible expected return for a given level of risk.

Investors should hold one of the optimal portfolios on the efficient frontier and adjust their total market risk by **leveraging** or deleveraging that portfolio with positions in the **risk-free asset**.

In a highly simplified world, the market portfolio sits on the efficient frontier, and all investors hold that portfolio, leveraged or deleveraged with positions in the risk-free asset.

Modern Portfolio Theory provides a broad context for understanding the interactions of **systematic risk** and reward. It has profoundly shaped how institutional portfolios are managed, and motivated the use of passive investment management techniques. The mathematics of MPT is used extensively in financial risk management.

2.3.2.4. Systematic Risk and Specific Risk

The **Capital Asset Pricing Model** (CAPM) divides the risk of holding risky assets into systematic and specific risk. Systematic risk is the risk of holding the **market portfolio**.

As the market moves, each individual asset is more or less affected. To the extent that any asset is affected by such general market moves, that asset entails systematic risk. Specific risk is the risk which is unique to an individual asset. It represents the component of an asset's volatility which is **uncorrelated** with general market moves.

The notions of specific and systematic risk also arise with risks that are not traded on financial markets. For example, when an insurance company sells homeowners insurance in a particular region, the insurer faces systematic risk from such risks as hurricanes or earthquakes. Such risks can impact many homes simultaneously. The insurer also faces specific risk from risks such as fires or lightning strikes—which just affect individual homes.

2.3.2.5. Efficient Frontier

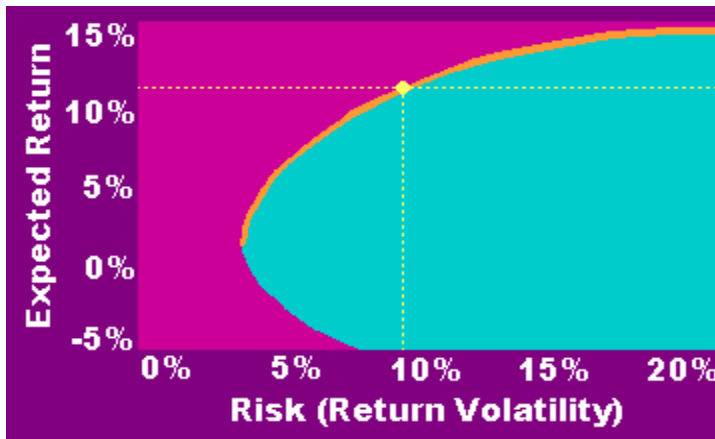
The efficient frontier is a notion from [Modern Portfolio Theory](#). That theory considers a universe of risky investments and explores what might be an optimal portfolio based upon those possible investments.

If we know the [expected returns](#), [volatilities](#) and [correlations](#) for all the investments in the universe, we can use that information to calculate the expected return and volatility of any portfolio that can be constructed using the instruments that comprise the universe.

The notion of "optimal" portfolio can be defined in one of two ways:

- 1) For any level of [market risk](#) (volatility) consider all the portfolios which have that volatility. From among them all, select the one which has the highest expected return.
- 2) For any expected return, consider all the portfolios which have that expected return. From among them all, select the one which has the lowest volatility.

Each definition produces a set of optimal portfolios. Definition (1) produces an optimal portfolio for each possible level of risk. Definition (2) produces an optimal portfolio for each expected return. Actually, the two definitions are equivalent. The set of optimal portfolios obtained using one definition is exactly the same set which is obtained from the other. That set of optimal portfolios is called the efficient frontier. This is illustrated in Figure 2.1 :



(Available at site <http://contingencyanalysis.com>)

Figure 2.1 Efficient Frontier

In Figure 2.1, the grey region corresponds to the achievable risk-return space. For every point in that region, there will be at least one portfolio which can be constructed from the investments in the universe and has the risk and return corresponding to that point. The black region is the unachievable risk-return space. No portfolios can be constructed corresponding to the points in this region. The curve in Figure 2.1 represents the efficient frontier.

The portfolios which correspond to points on that curve are optimal according to both definitions (1) and (2) above. For example, consider the point on the efficient frontier. Of all the portfolios having a 15% volatility, the portfolio corresponding to the point has the highest expected return. Correspondingly, of all the portfolios having a 14% expected return, the one corresponding to the point on the curve has the lowest volatility.

Typically, the portfolios which comprise the efficient frontier are the ones which are most highly **diversified**. Less diversified portfolios tend to be closer to the middle of the achievable region.

2.3.2.6. Risk-Free Rate

The risk-free rate is a theoretical interest rate at which an investment may earn interest without incurring any risk. The notion is used extensively in [option pricing theory](#) where [derivatives](#) are valued with a [risk neutral](#) assumption under which all assets may be assumed to have [expected returns](#) equal to the risk-free rate. The notion of a risk-free rate is also used in [Modern Portfolio Theory](#).

In practice, the risk-free rate is often assumed to be a short-term Treasury rate.

2.3.2.7. Diversification

[Volatilities](#) of [uncorrelated](#) risks do not add directly. When two or more uncorrelated risks are taken simultaneously, the volatility of the entire portfolio of risks is less than the sum of the individual risks' volatilities. Because the individual risks are uncorrelated, they tend to randomly dampen one another.

[Expected returns](#), on the other had, do add directly. If multiple risks are taken simultaneously, the expected return for the portfolio of risks is simply the sum of the expected returns for taking each of the risks individually.

This is illustrated for three uncorrelated risks in Equations [1] and [2]:

$$\sigma_{1+2+3} < \sigma_1 + \sigma_2 + \sigma_3 \quad [1]$$

$$\mu_{1+2+3} = \mu_1 + \mu_2 + \mu_3 \quad [2]$$

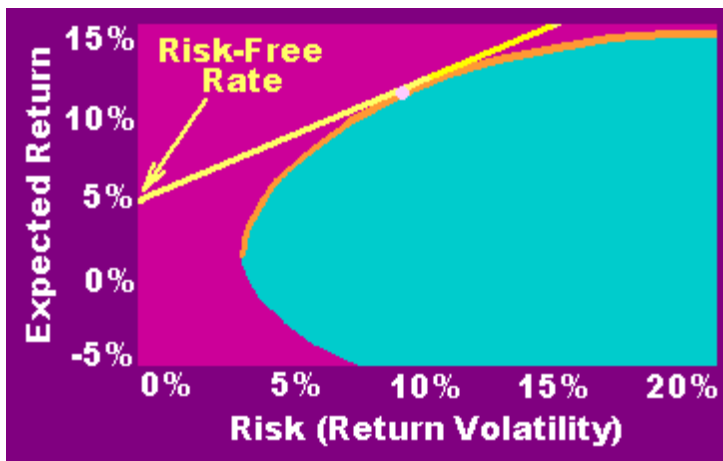
where σ denotes volatility and μ denotes expected return.

Accordingly, a portfolio which is invested in multiple uncorrelated risks will have an expected return which is commensurate with those of the individual risks taken, but a volatility which is less than commensurate with those of the individual risks.

Investors and other risk takers diversify their [exposures](#) by dividing their capital among multiple, uncorrelated risks. By doing so, they reduce their risk without reducing their expected returns.

2.3.2.8. Capital Market Line

James Tobin added the notion of leverage to **Modern Portfolio Theory** by incorporating into the analysis an asset which pays a **risk-free rate** of return. By combining a risk-free asset with risky assets, it is possible to construct portfolios whose risk-return profiles are superior to those of portfolios on the **efficient frontier**. Consider Figure 2.2:



(Available at site <http://contingencyanalysis.com>)

Figure 2.2 Capital Market Line

In Figure 2.2 , the risk-free rate is assumed to be 5%, and a tangent line—called the capital market line—has been drawn to the efficient frontier passing through the risk-free rate. The point of tangency corresponds to a portfolio on the efficient frontier. That portfolio is called the "super efficient" portfolio. The **Capital Asset Pricing Model** demonstrates that, given certain simplifying assumptions, the super-efficient portfolio must be the **market portfolio**.

Using the risk-free asset, investors who hold the super-efficient portfolio may:

- **Leverage** their position by shorting the risk-free asset and investing the proceeds in additional holdings in the super-efficient portfolio, or
- Deleverage their position by selling some of their holdings in the super-efficient portfolio and investing the proceeds in the risk-free asset.

The portfolios which result have risk-reward profiles which all fall on the capital market line. Accordingly, portfolios which combine the risk free asset with the super-

efficient portfolio are superior from a risk-reward standpoint to the portfolios on the efficient frontier.

2.3.2.9. Market Portfolio

The market portfolio is a theoretical notion used in [Modern Portfolio Theory](#). Out of the universe of risky investments available to an investor, the market portfolio is a portfolio consisting of every issue weighted proportionally to the total [market value](#) of that issue outstanding in the market.

For example, if we considered all the stocks that comprise the S&P 500 to represent our universe, then a (market capitalization weighted) S&P 500 index fund would represent the market portfolio.

2.3.2.10. Leverage and Diversification

Leverage is any process that compounds a risk. More specifically, it is any process that increases [exposure](#) to a source of risk. [Derivative](#) instruments are effective tools for leveraging a portfolio because they provide exposure to an [underlier](#) for little or no capital investment. Purchasing securities with borrowed funds is another convenient means of leveraging a portfolio.

[Repos](#) can be used to leverage a portfolio. By repaying a security, an investor retains market exposure to that security, while generating cash—effectively a loan. That cash can be invested in more securities, leveraging the original securities holdings. This strategy played a significant role in causing the bankruptcy of Orange County in 1994.

This is a simple paper which makes a serious point: Diversification is occasionally used as justification for novel or risky investment strategies. Often, the argument is flawed. [Diversification](#) is a vehicle for reducing portfolio risk without affecting [expected returns](#). Indeed, many novel or risky investments are justified because of their diversification potential.

[Leverage](#), however, can undo the benefits of diversification. In the past, this was not a problem because opportunities for leverage were limited. Today, however, derivative instruments and other financial transactions provide numerous opportunities to leverage a portfolio. This changes the mathematics of diversification. No longer does diversification necessarily reduce risk. Sometimes, it actually increases it.

3. CREDIT RISK

3.1. Benefits of the Credit Risk Management Models

Credit risk management models have gained widespread attention because they provide bank management with a more robust measure of the inherent risk in their institution and allows for a more timely and consistence means of measuring and managing risk. The models provide the following benefits;

- Banks' credit exposures typically cut across geographical locations and product lines. The use of credit risk models offers banks a framework for examining this risk in a timely manner, centralizing data on global exposures and analyzing marginal and absolute contributions to risk. These properties of models may contribute to an improvement in a bank's overall ability to identify, measure and manage risk.
- Credit risk models may provide estimates of credit risks such as unexpected losses, which reflect individual portfolio composition; hence, they may provide a better reflection of concentration risk compared to non-portfolio approaches.
- By design, models may be both influenced by, and be responsive to, shifts in business lines, credit quality, market variables and the economic environment. Consequently, modeling methodology holds out the possibility of providing a more responsive and informative tool for risk management.
- Models may offer (a) the incentive to improve systems and data collection efforts; (b) a more informed setting of limits and reserves; (c) more accurate risk-and performance-based pricing, which may contribute to a more transparent decision-making process and (d) a more consistent basis for economic capital allocation.
- From a supervisory perspective, the development of modeling methodology also hold significant appeal due to the models-based approach may bring capital requirements into closer alignment with the perceived riskiness of underlying assets and portfolio concentrations. As such, it may allow more comprehensive measure of capital requirements for credit risk and an improved distribution of capital within the financial system. Furthermore, the flexibility of models in adapting to changes in the economic environment and

innovations in financial products may reduce the incentive for banks to engage in regulatory capital arbitrage (Basle Committee on Banking Supervision, 1999).

- They are more comprehensive and consistent measure of risk. Credit risk models can be a more effective risk measurement and management tool given their ability to quickly measure risk, taking into account an institution's internal risk management structure, portfolio composition and diversification, term structure, credit offsets, and collateral support.
- Credit risk management models are more timely and objective measure of risk. Credit risk models strengthen existing risk management practices by providing management with an independent but more accurate, timely, and consistent measure of credit risk.
- These models are more flexible approach to risk management. Credit risk management models provide management the flexibility to design a risk measurement and management tool that can be tailored to the specific risks inherent in its portfolio. These result can be easily aggregated across risk taking units and across financial institutions worldwide, providing a more accurate and comprehensive measure of risk.
- Models improve the transparency between the various credit risk activities. While management looks to limits, credit reserves and the allocation of economic capital as a means of controlling and managing risk, it is not readily apparent how the data elements of these activities are linked with one other. If credit models were fully integrated into the daily risk management activities, the link between these activities would be more readily apparent (GARP the Committee on Regulation and Supervision, 1999).

3.2. Application Areas of Credit Risk Management Models

Credit risk modeling methodologies allow a tailored and flexible approach to price measurement and risk management. Models are, by design, both influenced by and responsive to shifts in business lines, credit quality, market variables and the economic environment. Furthermore, models allow banks to analyze marginal and absolute contributions to risk, and reflect concentration risk within a portfolio. These properties of models may contribute to an improvement in a bank's overall credit culture.

Current applications of credit risk models included;

- Setting of concentration and exposure limits,
- Setting of hold targets on syndicated loans,
- Risk-based pricing,
- Improving the risk/return profiles of the portfolio,
- Evaluation of risk-adjusted performance of business lines or managers using risk-adjusted return on capital,
- Economic capital allocation,

To attain these targets, financial institutions need sound and robust models, and methodologies.

Table 3.1 Comparison of Value at Risk to Credit Risk

Item	Value at Risk	Credit Risk
Source of Risk	Market Risk	Market Risk and Default
Unit to which risk limits apply	Some level of trading organization	Legal Entity of counterparty
Time horizon	Short(days)	Potentially long(years)
Legal issues	Not applicable	Very important

(Jorion, 1997)

3.4. Mitigating Credit Risk

Derivative contracts can be traded either on organized exchanges or over a decentralized network of financial institutions, typically called over-the-counter(OTC) markets. Each market has developed its own techniques to deal with credit risk. These methods must be formally modeled when assessing possible losses from default.

3.5. Modeling Credit Risk

Credit risk depends on a number of factors:

- the current fair value of the contracts,
- the potential future credit exposure, the extent to which netting arrangements and collateral can effectively reduce exposure,
- and the likelihood of default by the customer.

The issue is how to model all of these factors into a quantitative measure of credit risk.

There has been a sudden change in the credit risk models after 1999. Especially with the BIS new regulations on Credit Risk standardization many of the banks and other institutions began to pay more attention to their credit risk measurement models.

BIS 1999 Regulation

Basle Committee on Banking Supervision:

Principle 11: Banks must have information systems and analytical techniques that enable management to measure credit risk.

Principle 10: Banks should develop and utilize internal risk rating systems in managing credit risk.

A bank should provide summary information about its internal rating process and the internal credit ratings of its credit exposure.

3.6. Basic Credit Risk Models

3.6.1. CreditMetrics

A borrower's default probability depends on the amount by which assets exceed liabilities, and the volatility of those assets. Critical values corresponding to each borrower are calculated than the joint probability is computed.

Portfolio Loss Distribution is calculated by Monte Carlo:

- Draw random correlated standard normal variables representing the change in asset value for each borrower.
- Sum the losses resulting from each credit rating change default.
- Repeat thousand of times to build a distribution of portfolio losses.

This model uses mark to market paradigm and transition matrix for rating migration and default probabilities that can be obtainable from different sources.

Table 3.2 One-Year Transition probabilities for BBB-rated Borrower

AAA	0,02 %
AA	0,33
A	5,95
BBB	86,93
BB	5,3
B	1,17
CCC	0,12
Default	0,18

(Gupton et al., 1997)

Table 3.3 Value for the Loan at the End of Year 1 Under Different Ratings

AAA	\$109,37
AA	109,19
A	108,66
BBB	107,55
BB	102,02
B	98,10
CCC	83,64
Default	51,13

(Gupton et al., 1997)

Calculating the credit VaR

If the loans are normally distributed. The % 5 loss case can be found as standard VaR.

CrVaR=1,65 standard deviation of loans.

In the above case CrVaR= \$ 4,93

However, assuming normality is problematic then one can use the actual distribution.

CreditMetrics is a Merton-based model, relying on Merton's model of a firm's capital structure a firm defaults when its asset value falls below its liabilities. A borrower's default probability then depends on the amount by which assets exceed liabilities, and the volatility of those assets (Kealhofer, 1998). If changes in asset value are normally distributed, the default probability can be expressed as the probability of a standard normal variable falling below some critical value. The first step in this model is then to calculate critical values corresponding to each borrower's default probability (mapped from the borrower's credit rating). Joint default events among borrowers in the portfolio are related to the extent that the borrowers' changes in asset value are correlated (input in the form of a pairwise correlation matrix determined according to country and industry groupings). The portfolio loss distribution is calculated by Monte Carlo simulation, as follows:

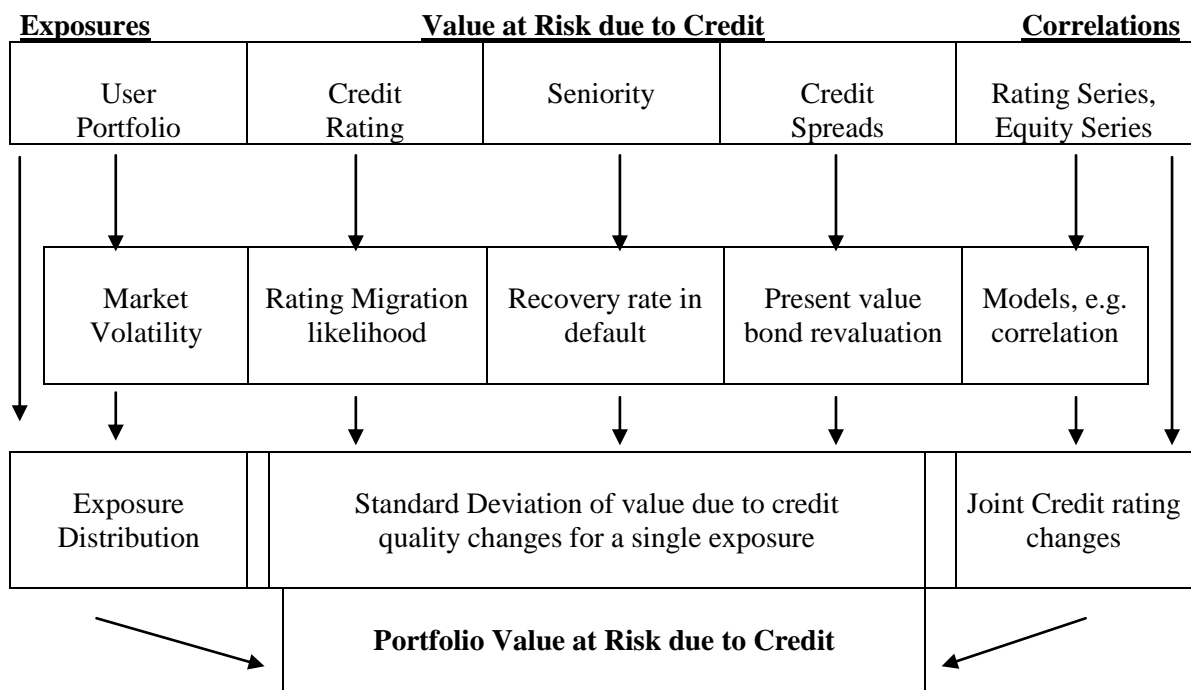
1. Draw random correlated standard normal variables representing the change in asset value for each borrower.
2. Compare this standardised change in asset value to the pre calculated critical value to determine credit rating change.
3. Sum the losses resulting from each credit rating change default to arrive at a total portfolio loss.
4. Repeat thousands of times to build a distribution of portfolio losses (Koyluoglu and Hickman, 1998).

Basic properties of the CreditMetrics (CM) can be listed as follows:

- CM can use different time horizons other than one-year time period (the transition matrix should, however, be estimated for the same time interval as the risk horizon over which we are interested in estimating risks. For instance, a semi-annual risk horizon would use a semi-annual rather than one-year

transition matrix. Also the other parameters must be estimated at the same time horizon correlations.)(Gupton et al., 1997).

- CM uses MTM paradigm to value the credit instruments. In fact, CM value the instruments with DCCF approach (to discount these instruments, for example, for the bonds, CM get the discount rate from the *forward zero curve* that extends from the end of the risk horizon to the maturity of the instrument) (Gupton et al.,1997).



(Gupton et al., 1997)

Figure 3.1.: Roadmap for the CreditMetrics Methodology

- Owing to the CM methodology is Merton-based; it uses asset correlation as the proxy for the default correlation.
- Due to MTM paradigm implemented by CM, it uses the transition matrix for rating migration and default probabilities that can be obtainable from different sources -e.g. S&P and Moody’s rating agencies or from KMV’s EDFs (data obtained from these sources should be calibrated according to the some rules). Also rating migrations can be calculated using the equity-based approach.

- As for the recovery rates, CM methodology employed the beta distribution for H estimating the recovery rate, so the volatility of recovery rate incorporated to the model).

3.6.1.1. Exposure types

CreditMetrics is capable of estimating most any credit risk type limited only by the data available to revalue exposures upon up (down)grade and default. Only the calculation of future values is different for different instrument categories. The likelihood of being in each credit quality state is the same for all instrument categories. It is included the following generic exposure types:

- **Non-interest bearing receivables (trade credit)** Receivables treated in the same way as the bonds. For receivables which become due beyond the risk horizon, the cash-flow is treated as if it were a zero coupon bond paying on the receivable date, and revalue the cash-flow based on the bond spreads in each rating category. If there were more applicable spreads available, specific to receivables, it would certainly be reasonable to use these in place of the bond spreads for the purposes of this revaluation. Often, a receivable will be due before the risk horizon. In this situation, it is not even necessary to revalue in different rating categories. Both the payment is made, and it is “revalued” at the receivables face amount, or there is default, and it is revalued based on some recovery rate.
- **Bonds and loans:** Due to MTM paradigm implemented by CM, bond’s value is calculated for each migration state (loans treated as bonds). Valuation falls into two categories: (1) in the event of *default*, (2) in the event of *up (down) grades*.

In the event of default, value of the bond would be given by its recovery value rate. Key variable in the event of default is the recovery rate. Recovery rates are not deterministic quantities but rather display a large amount of variation. This variation of value in the case of default is a significant contributor to risk. To model this variation, the mean and standard deviation of recovery rate for each issue in portfolio is obtained according to the issue’s seniority. For example, in BBB rated senior unsecured issue, the recovery mean is 53% and the recovery standard deviation is 33%. For each default

scenario, it is generated a random recovery rate according to a beta distribution with these parameters. These recovery rates then help to obtain the value in each default scenario (Gupton et al., 1997).

- **Commitments to lend** A loan commitment is composed of a drawn and undrawn portion. The drawdown on the loan commitment is the amount currently borrowed. Interest is paid on the drawn portion, and a fee is paid on the undrawn portion. When revaluing a loan commitment given a credit rating change, the changes in value to both portions must be therefore accounted for. The drawn portion is revalued exactly like a loan. To this it is added the change in value of the undrawn portion (Gupton et al., 1997).

Because loan commitments give the obligor the option of changing the size of a loan, loan commitments can dynamically change the portfolio composition. The amount drawn down at the risk horizon is closely related to the credit rating of the obligor. For example, if an obligor deteriorates, it is likely to draw down additional funds. On the other hand, if its prospects improve, it is unlikely to need the extra borrowing (Gupton et al., 1997).

The worst possible case for a commitment is that the counterparty draws down the full amount and then defaults. It is intuitive, then, to treat a commitment as if it were a loan, with principal equal to the full commitment line. This is certainly the simplest approach to commitments, and from a risk perspective, the most conservative (Gupton et al., 1997).

In order to model commitments more accurately, it is necessary to estimate not only the amount of the commitment which will be drawn down in the case of default, but also the amount which will be drawn down (or paid back) as the counterparty undergoes credit rating changes. For this purpose CM methodology uses the data of *average commitment usage and usage of the normally unused commitment in the event of default*. By the help of these data, it can be reached the values of the commitments in both situations (Gupton et al., 1997).

- **Financial letters of credit: In all the cases where there can be a default:** there will also be full exposure just like a loan. Letter of credits can be treated identically to loans, including the use of the credit spread curves and recovery rates that have been estimated for loans (Gupton et al., 1997).

- **Market-driven instruments:** In these transactions (e.g. swaps, forwards etc.), credit risk and market risk components are intimately coupled because of an inherent optionality. This optionality stems from the fact that it can be a loss on the transaction if the counterparty defaults only if instruments are in-the-money (i.e., the obligor owes money on a net present value basis). Credit loss occurs when both of the following two conditions are satisfied:
 - The counterparty undergoes a credit quality change.
 - The transaction is out-of-the-money for the counterparty; that is, the counterparty owes money on the transaction on a net present value basis.

Essentially, the value of the transaction as a difference of two components:

- The first component is equal to the forward *risk-free* value of the instrument cash flows. This hypothetical value is obtained by finding the forward value of the instruments cash flows by using the government rates rather than the instruments rates; therefore the first component is the same for all forward credit rating states (Gupton et al., 1997).
- The second component represents the loss expected on the instrument due to a default net of recoveries by the counterparty on their remaining cash flows of the instrument. By “remaining” it is meant all cash flows that occur after the risk horizon (assumed to be one year). Since the probability of this default varies by rating category, the second component varies from one rating category to another (Gupton et al., 1997). Finally, the revaluation of the instrument in any rating category is obtained by subtracting the *second* (expected default loss) component from *the first* (risk-free value) component (Gupton et al., 1997).

3.6.1.2. Credit risk calculation

For a single asset (so called stand-alone risk in CM), calculation of credit risk is a simple issue as can be seen from the figure 3.1. According to the roadmap of CM, three steps are necessary, these are:

Step 1: The credit rating of borrower based on seniority determines the chance of the borrower either defaulting or migrating to any possible credit quality state at the risk horizon (i.e. rating migration probabilities read from transition matrix).

Step 2: The seniority of the instruments determines its recovery rate in the case of default. The forward zero curve (or other valuation factors depending on the instrument's type) for each credit rating category determines the value of the instruments upon up(down)grade. Both of these aid revaluation of the instruments.

Step 3: The likelihood from Step 1 and the values from Step 2 then combine in our calculation of volatility of value due to credit quality changes (Gupton et al., 1997).

3.6.2. Credit Risk+ Model

Major difference between CR+ and C-Metrics

- CR+ is a Default Model rather than Mark to Market model as C-Metrics
- Two state of the worlds are assumed default non-default
- C-Metrics default problem is discrete(upgrade/downgrade) whereas CR+ it is modeled as a cotinuous function.
- Two parameters affect the credit loss
 - a)the frequency of defaults
 - b)severity of losses.

3.6.2.1. Distribution of Losses

Since the distribution of losses can not be modeled by a symetric distribution, position distribution is assumed where the mean default rate equals to its variance.

$$P(n \text{ defaults}) = (e^{-\lambda} \lambda^n) / n!$$

N = number of defaults of interest, n=1,2,...N

λ = mean number of defaults.

If we use the bands of \$ 20.000.- than the 99th percentile of unexpected credit loss can be calculated straightforwardly.

For example if we have on average a 3 % loans with(a value of \$ 20.000.-) ended with default then “ 3 “ can be found. Then 99 % confident losses with a value of \$ 20.000.- will hint us a value of 8 defaults (or \$ 160.000.- loss). Then the required capital would be \$ 100.000.- since expected loss = \$ 60.000.- and the wost case will be \$ 160.000.-.

Advantage : It doesn't require any type of credit spreads.

Disadvantage: Since it doesn't depend on mark to market model it can not assess the value of loan changes.

The CreditRisk+ (CR+) is a model of default risk. Each obligor has only two possible end-of-period states, default and non-default. In the event of default, the lender suffers a loss of fixed size; this is the lender's exposure to the obligor. The distributional assumptions and functional forms imposed by CR allow the distribution of total portfolio losses to be calculated in a convenient analytic form (Gordy, 1998).

CR+ is based on a portfolio approach to modelling credit default risk that takes into account information relating to size and maturity of an exposure and the credit quality and systematic risk of an obligor.

The CR+ model is a statistical model of credit default risk that makes no assumptions about the causes of default. This approach is similar to that taken in market risk management, where no attempt is made to model the causes of market price movements. The CR model considers default rates as *continuous* random variables and incorporates the volatility of default rates in order to capture the uncertainty in the level of default rates. Often, background factors, such as the state of the economy, may cause the incidence of defaults to be correlated; the effects of these background factors are incorporated into the CR model through the use of *default rate volatility* and *sector analysis* rather than using default correlations as explicit inputs into the model (Credit Suisse Financial ProductsCSFP, 1997).

Mathematical techniques applied widely in the insurance industry are used to model the sudden event of obligor default. Applying insurance modelling techniques, the analytic CR model captures the essential characteristics of credit default events and allows explicit calculation of a full loss distribution for a portfolio of credit exposures (CSFP, 1997).

CREDIT RISK +			
Credit Risk Measurement		Economic Capital	Applications
Exposures	Default Rates	Credit Default Loss Distribution	Provisioning
Recovery Rates	Default Rate Volatility	Scenario Analysis	Limits
Credit Risk+ Model			Portfolio management

(CSFP, 1997)

Figure 3.2 Components of CreditRisk+ Methodology

CR+ reflects the requirements of a modern approach to managing credit risk and comprises three main components.

- The CR+ model that uses a portfolio approach and analytical techniques applied widely in the insurance industry.
- A methodology for calculating economic capital for credit risk.
- Applications of the credit risk modelling, methodology including: **(i)** a methodology for establishing provisions on an anticipatory basis, and **(ii)** a means of measuring diversification and concentration to assist in portfolio management(CSFP, 1997).

3.6.2.2. Basic properties of the CR+ model

CR+ model calculates loss distribution by analytical approach —so called closed form formulation (i.e. loss distribution can be found by standard formulation of the portfolio, not by the help of simulation). The basic characteristics of the CR model are as follows:

- CR+ uses different time horizon other than one year for credit risk. The CR+ model can be used to calculate multi-year loss distributions by decomposing the exposure profile over time into separate elements of discrete time, with the present value of the remaining exposure in each time period being assigned a marginal default probability relevant to the maturity and credit quality. These decomposed exposure elements can then be used by the CR+ model to generate a loss distribution on a hold-to-maturity basis (CSFP, 1997).
- CR+ model uses DM paradigm to value the credit instruments.
- The CR+ model is a statistical model of credit default risk that models default rates as continuous random variables and incorporates the volatility of the default rate in order to capture the uncertainty in the level of the default rate. The default probabilities are not constant over time, but rather increase or decrease in response to background macroeconomic factors. To the extent that two obligors are sensitive to

the same set of background factors, their default probabilities will move together. These movements in probability give rise to correlations in defaults (Gordy, 1998).

- Treating the default rate as a random variable common to multiple borrowers incorporates joint-default behaviour of borrowers. Borrowers are allocated amongst “sectors” each of which has a mean default rate and a default rate volatility. The default rate volatility is the standard deviation, which would be observed on an infinitely diversified homogeneous portfolio of borrowers in the sector (Koyluoglu and Hickman, 1998).
- The CR+ model is capable of handling all types of instruments that give rise to credit exposure, including bonds, loans, commitments, financial letters of credit and derivative exposures. For some of these transaction types, it is necessary to make an assumption about the level of exposure in the event of a default: for example, a financial letter of credit will usually be drawn down prior to default and therefore the exposure at risk should be assumed to be the full nominal amount. In addition, if a multi-year time horizon is being used, it is important that the changing exposures over time are accurately captured (CSFP, 1997).
- It is possible to incorporate the effects of background factors into the specification of default rates by allowing the default rate itself to have a probability distribution. This is accomplished by incorporating default rate volatility into the model. The CR+ model models the effects of background factors by using default rate volatility that result in increased defaults rather than by using default correlations as a direct input. Both approaches, the use of default rate volatility and default correlations, give rise to loss distributions with fat tails. The CR+ model does not attempt to model correlations explicitly but captures the same concentration effects through the use of default rate volatility and sector analysis (CSFP, 1997).

- In order to recognise some of the diversification benefit of obligors whose fortunes are affected by a number of independent systematic factors, it can be assumed that each obligor is subject to only one systematic factor, which is responsible for all of the uncertainty of the obligor's default rate. For example, obligors could be allocated to sectors according to their country of domicile. Once allocated to a sector, the obligor's default rate and default rate volatility is set individually. In this case, a sector can be thought of as a collection of obligors having the common property that they are influenced by the same single systematic factor (CSFP, 1997).

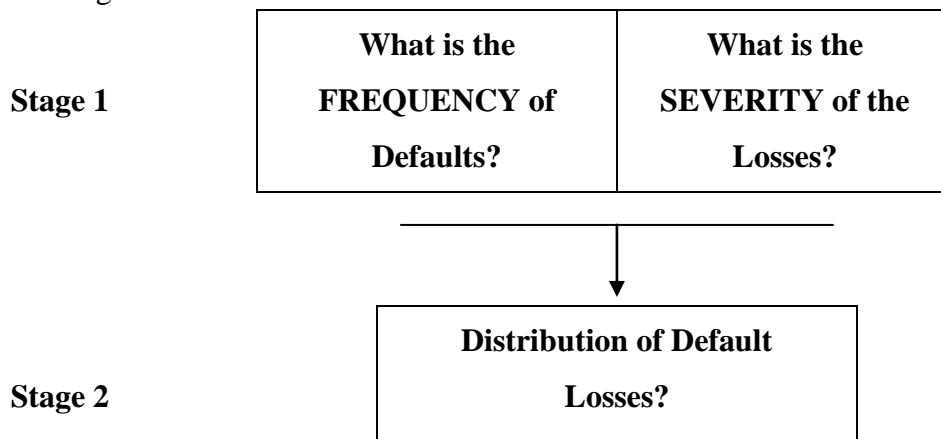
After the brief information about CR+ methodology, rest of this section explains the other details of the model as to how loss distribution can be calculated and how the parameters are estimated.

3.6.2.3. Loss distribution

Owing to the CR+ model uses DM paradigm to value the different type of financial instruments, it is simple case to find the each obligor's exposure (see section 4.8. DM paradigm). The other inputs of the model to find the loss distribution are

- (a) Unconditional default rates (which can be obtainable from different sources mentioned before),
- (b) Default rate volatility,
- (c) Recovery rates.

Two stages needed to find the loss distribution:



(CSFP, 1997)

Figure 3.3 Two Stages of Default Losses

The CR+ model makes no assumption about the causes of default. Credit defaults occur as a sequence of events in such a way that it is neither possible to forecast the exact time of occurrence of any one default nor the exact total number of defaults. There is exposure to default losses from a large number of obligors and the probability of default by any particular obligor is small. This situation is well represented by the Poisson distribution (CSFP, 1997).

It is considered first the distribution of the number of default events in a time period, such as one year, within a portfolio of obligors having a range of different annual probabilities of default. The annual probability of default of each obligor can be conveniently determined by its credit rating and a mapping between default rates and credit ratings. If the volatility of the default rate is not incorporated, the Poisson distribution will closely approximate the distribution of the number of default events. This is regardless of the individual default rate for a particular obligor. The CR model models the underlying default rates by specifying a default rate and a default rate volatility. These aims to take account of the variation in default rates in a pragmatic manner, without introducing significant model error (CSFP, 1997).

Given the number of default events, it is considered the distribution of losses in the portfolio. The distribution of losses differs from the distribution of default events because the amount lost in a given default depends on the exposure of the individual obligors. Unlike the variation of default probability between obligors, which does not influence the distribution of the total number of defaults, the variation in exposure magnitude results in a loss distribution that is not Poisson in general. Moreover, information about the distribution of different exposures is essential to the overall distribution. However, it is impossible to describe the overall distribution of losses because its probability generating function has a simple closed form amenable to computation (CSFP, 1997).

In the event of default of an obligor, a firm generally incurs a loss equal to the amount owed by the obligor less a recovery amount. A recovery rate is used to quantify the amount received from this process. Recovery rates should take account of the seniority of the obligation and any collateral or security held (CSFP, 1997).

In order to reduce the amount of data to be processed, two steps are followed:

- The exposures are adjusted by anticipated recovery rates in order to calculate the loss in a given default.
- The exposures, net of the above recovery adjustment, are divided into bands of exposure with the level of exposure in each band being approximated by a common average (CSFP, 1997).

The CR+ model calculates the probability that a loss of a certain multiple of the chosen unit of exposure will occur. This allows a full loss distribution to be generated. After the loss distribution is obtained, then the statistics related to the portfolio can be calculated by the standard formulas. Next section explains to estimate the parameters needed for loss distribution.

3.6.2.4. Parameter estimation

When estimating the parameters, keep in mind that the key assumptions of the CR+ model are:

- Default rates are stochastic,
- The level of default rates affects the incidence of default events but there is no causal relationship between the events (CSFP, 1997).

In order to facilitate the explanation of the CR+ model, it is first considered the case in which the mean default rate for each obligor in the portfolio is fixed. Then it is generalised the technique to the case in which the mean default rate is stochastic.

3.6.2.5. Comparison of two models by parameters

CreditMetrics and Credit Risk+ differ in distributional assumptions and functional forms, solution techniques, suggested methods for calibration, and mathematical language. As the preceding analysis makes clear, only the differences in distributional assumptions and functional forms are fundamental. Each model can be mapped into the mathematical language of the other, which demonstrates that the difference between the latent variable representation of CreditMetrics and the covering default probabilities of CreditRisk+ is one of presentation and not substance (Gordy, 1998).

By contrast, distributional assumptions and functional forms are model primitives. In each model, the choice of distribution for the systemic risk factors and the functional form for the conditional default probabilities together give shape to the joint distribution over obligor defaults in the portfolio. The CreditMetrics specifications of normally distributed the systemic risk factors and the conditional default probabilities may be somewhat arbitrary, but nonetheless strongly influence the results. One could substitute, say, a multivariate t distribution for the normal distribution, and still employ the Monte Carlo methodology of CreditMetrics. However, even if parameters were recalibrated to yield the same mean and variance of portfolio loss, the overall shape of the loss distribution would differ, and therefore the tail percentile values would change as well. The choice of the gamma distribution and the function form for conditional default probabilities are similarly characteristic of CreditRisk+ (Gordy, 1998).

Remaining differences between the two models are attributable to differences in solution method. The Monte Carlo method of CreditMetrics is flexible but computationally intensive. CreditRisk+ offers the efficiency of a closed-form solution, but at the expense of additional restrictions or approximations. In particular,

- CreditMetrics allows naturally for multi-state outcomes and for uncertainty in recoveries, whereas the closed-form CreditRisk+ is a two-state model with fixed recovery rates.
- CreditRisk+ imposes a “Poisson approximation” on the conditional distribution of defaults.
- CreditRisk+ rounds each obligor’s loan loss exposure to the nearest element in a finite set of values (Gordy, 1998).

3.6.2.6. Default Mode Paradigm(DM) and Mark-to-market Paradigm (MTM)

The DM paradigm is the most common approach used by banks for defining credit losses. It is sometimes called a two-state model because only two outcomes are relevant: non-default and default. If the loan does not default, there is no credit loss. If the loan defaults, there, generally is a credit loss, equal to the present value of the difference between the customer’s contractual obligations and the loan’s actual cash-flows over the workout period.

In contrast to the DM paradigm, within the MTM paradigm a credit loss can arise in response to deterioration in an asset's credit quality short of default. In effect, the MTM paradigm treats the credit portfolio as being marked to market (or, more accurately, marked to model) at the beginning and end of the planning horizon, with the concept of credit loss reflecting the difference between these valuations.

The MTM paradigm generalizes the DM approach by recognizing that the economic value of a credit instrument may decline even if the counterparty does not formally default within the planning horizon. The MTM model is "multi-state" in that "default" is only one of several possible credit rating grades to which the instrument could migrate over the planning horizon (Jones and Mingo, 1998).

MTM-type models recognize that changes in an asset's creditworthiness, and its potential impact on a bank's financial position, may occur due to events short of default. Hence, in addition to EDFs, these models must also incorporate (through the rating transition matrix) the probabilities of credit rating migrations to non-default states. Given the rating transition matrix associated with each customer, Monte Carlo methods are generally used to simulate migration paths for each credit position in the portfolio. For each position, the simulated migration (and the risk premium associated with the instrument's end-of-period rating grade) is used, in effect, to mark the position to market as of the end of the time horizon (Basel Committee on Banking Supervision, 1999a).

To illustrate the differences between the DM and MTM paradigms, consider a loan having an internal credit rating equivalent to BBB. Under both paradigms, the loan could lose value if it were to default during the planning horizon. In this event, the rate of credit loss would be represented by the loan's LGD. Under the MTM paradigm, however, credit losses also could arise if the loan were to suffer a downgrade short of default (e.g., migrate from BBB to BB), or if credit risk spreads prevailing in financial markets were to increase over the planning horizon. Conversely, the value of the loan could increase (implying an economic gain, rather than a loss) if its credit rating improved or if credit spreads narrowed (Jones and Mingo, 1998).

- **Valuation models** : Most MTM-type credit models employ either a discounted contractual cash flow (DCCF) approach or a risk-neutral valuation (RNV) approach for purposes of modelling the current and future (mark-to-market) values of credit instruments.

- **Discounted contractual cash flow approach** : The current value of a loan that has not defaulted is represented as the present discounted value of its future contractual cash flows. For a loan having a particular internal risk rating (comparable to, say, BBB), the credit spreads used in discounting the contractual cash flows would equal the market-determined term structure of credit spreads associated with corporate bonds having that same grade. The current value of a loan would be treated as known, while its future value would depend on its uncertain end-of-period risk rating and the term structure of credit spreads associated with that rating. Thus, the value of a loan can change over the time horizon, reflecting either a migration of the borrower to a different risk rating grade or a change in the market-determined term structure of credit spreads. One of the rating grades to which a loan can migrate over the planning horizon is "default". Obviously, the present value of a defaulted loan would not be based on the discounting of contractual cash flows. Rather, as with DM-type models, in the event of default, the future value of a loan (in dollar terms) would be given by its recovery value, equal to one minus the LGD (Basel Committee on Banking Supervision, 1999a).

- **Risk-neutral valuation approach** ; Although it is easily understood and implemented, the DCCF approach is not fully consistent with modern finance theory. Typically, identical discount rates are assigned to all loans to firms having the same internal risk rating or EDF. Consequently, if a firm has not defaulted as of the planning horizon, the future values of its loans do not depend on the expected LGDs of the loans. Senior and subordinated loans to a single firm would have the same future discount price, regardless of differences in expected recovery in the event of future default. Furthermore, finance theory holds that the value of an asset depends on the correlation of its return with that of the market. Under DCCF, however, loans to two identically rated firms receive the same discount rates, even if the two firms are not equally sensitive to the business cycle or to other systematic factors.

In this framework, a firm goes into default when the value of its underlying assets falls beneath the level needed to support its debt. Instead of discounting *contractual* payments, the **RNV** method discounts *contingent* payments: if a payment is contractually due at date t , the payment actually received by the lender will be the contractual amount only if the firm has not defaulted by date t ; the lender receives a portion of the loan's face value equal to $1-LGD$ if the borrower defaults at date t , and the lender receives nothing at date t if the borrower has defaulted prior to date t . A loan can thus be viewed as a set of derivative contracts on the underlying value of the borrower's assets. The value of the loan equals the sum of the present values of these derivative contracts. The discount rate applied to the contracts' contingent cash flows is determined using the risk-free term structure of interest rates and the risk-neutral pricing measure. Intuitively, the risk-neutral pricing measure can be thought of as an adjustment to the probabilities of borrower default at each horizon, which incorporates the market risk premium associated with the borrower's default risk. The size of the adjustment depends on the expected return and volatility of the borrower's asset value. If asset return is modeled consistent with the Capital Asset Pricing Model (CAPM) framework, then the expected return can be expressed in terms of the *market* expected return and the firm's correlation with the market. Thus, consistent with standard finance theory, the pricing of loans under RNV adjusts not only for the EDF and LGD of the borrower, but also for the correlation between borrower risk and systematic risk (Basel Committee on Banking Supervision, 1999a).

- **Calculation of PDF** : Given the rating transition matrix associated with each customer, Monte Carlo methods are generally used to simulate PDF. The Monte Carlo techniques employed in credit risk modeling are essentially identical to those used within VaR models in the trading account, and are not discussed here.

The dichotomy between the DCCF and RNV approaches to pricing may be sharper in theory than in practice. In each methodology, a loan's value is constructed as a discounted

present value of its future cash flows. The approaches differ mainly in how the discount factors are calculated. The DCCF method takes a nonparametric approach to estimating these discount factors. Public issuers of debt are grouped into rating spreads on the issuers are then averaged within each "bucket". The RNV method is highly structural - it imposes a model that prices each loan simultaneously in a unified framework. In practice, the calibration of the market risk model typically makes use of credit spreads from the debt market (Basel Committee Banking Supervision, 1999a).

Nonetheless, if debt markets are reasonably efficient and the assumptions of RNV model are approximately valid, then the two methods ought to produce similar aggregate values for well-diversified portfolios. Also BIS expressed one key issue as to DCCF versus RNV: the choice of DCCF versus RNV pricing models seems to be a tradeoff between sensitivity to data input quality on the one hand, and model assumptions on the other hand. In other words, the choice is empirical issue (Basel Committee on Banking Supervision, 1999a).

3.6.3. McKinsey Credit Portfolio Review

It differs from the others by

- models actual, discrete loss distributions depending on number and size of credits,
- it is a mixture of default and Mark to market model,
- tabulated loss distributions are driven by the state of the economy,
- specific country and industry influences are explicitly recognized empirical relationship.

Model: probability of a loan to default has the following functional form:

$$P_t = f(Y_t)$$

Where the P is a logistic function.

3.6.4. KMV's Portfolio Manager

The main **advantage** of KMV is its dynamic nature where a change in stock prices and other changes of the firm are reflected in Expected Default probability of the firm. (In theory EDF scores of a firm can be updated within a day).

Disadvantage: Normality assumption.

4. RISK RATINGS

4.1. Introduction to the Risk Ratings

Tecniques, practices, and tools for credit risk management are evolving rapidly, as are the challenges that banking organizations face in their business lending activities. For larger institutions, the number and geographic dispersions of their borrowers make it increasingly difficult for such institutions to manage their loan porfolios simply by remaining closely attuned to the performance of each borrower. As a result, one increasingly important component of the systems for controlling credit risk at larger institutions is the identification of gradation in credit risk among their business loans, and assignment of internal credit risk ratings to loans that correspond to the these gradations. The use of such an internal rating process is appropriate and, indeed, necessary for sound risk management at large institutions(Treacy and Carey, 1998).

Internal credit ratings are becoming increasingly important in credit risk management at large banks. Banks' internal risk ratings summerize the risk of loss due to failure by a given borrower to pay as promised(Treacy and Carey, 1998). Accurate, consistent loan grading, or risk rating, is essential underpinning of sophisticated credit risk management. For large banks, whose commercial borrowers may number in the tens thousands, internal ratings are an essential ingredient in effective credit risk management. Without the distillation of information that ratings represent, any comparison of the risk posed by such a large number of borrowers would be extremely difficult because of the need to simultaneously consider many risk factors for each of the many borrowers(Treacy and Carey, 1998).

As with all material bank activities, a sound risk management process should adequately illuminate the risk being taken and apply appropriate controls to allow the institution to balance risks against returns and the institution's overall appetite for risk, giving due consideration to the uncertainties faced by lenders and the long-term viability of the bank. Accordingly, large banking organizations should have strong risk rating systems(Treacy, 1998).

In short, risk ratings are the primary summary indicator of risk for banks' individual credit exposures. They both shape and reflect the nature of credit decisions that banks make daily. Understanding how rating systems are conceptualized, designed,

operated, and used in risk management is thus essential to understanding how banks perform to control risk exposures (Treacy and Carey, 1998).

Before beginning to express the credit risk ratings, it is important to mention that to reach the final credit score various techniques are used including subjective judgement the experienced bank staff or statistical models, but neither subjective judgements nor statistical models are alone sufficient enough to find out the correct risk ratings, they must be implemented together due to both having the disadvantages and advantages.

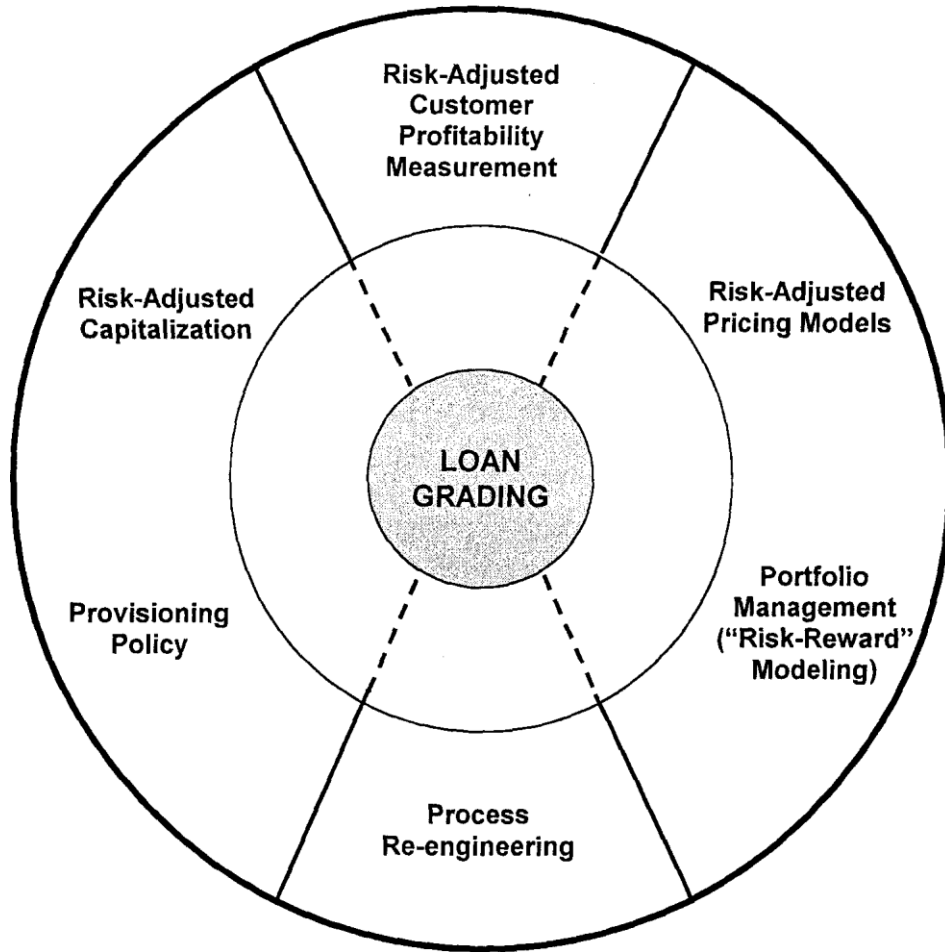
4.2. Implementation Areas of Internal Risk Ratings

Internal rating systems are currently being used at large institutions for a range of purposes. At one end of this range they are primarily used to determine approval requirements and identify problem loans, while at the other they are also an integral element of credit portfolio monitoring and management, capital allocation, credit pricing, profitability analysis, and detailed analysis to support loan loss reserving. Internal rating systems being used for the latter purposes should be significantly richer and more robust than systems used for the former purposes. These systems should take proper account of gradations in risk and the overall composition of portfolios in originating new loans, assessing overall portfolio risks and concentrations, and reporting on risk profiles to directors and management. Moreover, such rating systems also should play an important role in establishing an appropriate level for the allowance for loan and lease losses, conducting internal bank analysis of loan and relationship profitability, assessing capital adequacy, and possibly performance-based compensation (Treacy, 1998).

Ratings are the foundation for a set of vital initiatives, these are;

- Assigning loss provisions and capital to loans,
- Developing a risk-adjusted customer profitability and pricing models,
- Managing the bank's risk-reward tradeoff,
- Reengineering credit processes to increase efficiency and lower loss potentials- determining the limits-

4.3. Architecture of Risk Rating Systems



(OWC Credit Comments, 1992)

Figure 4.1 Application Areas of Risk Ratings

In choosing the architecture of its risk rating system, a bank must decide which loss concepts to employ, the number and meaning of grades on the rating scale corresponding to each loss concept, and whether to include “watch” and “regulatory” grades on such scales. The choices made and reasons for them vary widely, but on the whole, the primary determinants of bank rating system architecture appear to be the bank’s mix of large and smaller borrowers and the extent to which the bank uses quantitative systems for credit risk management and profitability analysis. In principle, banks must also decide whether to grade borrowers according to their current condition or their expected condition under stress (Treacy and Carey, 1998).

4.3.1. Loss Concept and Implementation

The credit risk of a loan or other exposure over a given period involves both the probability of default (PD) and the fraction of the loan's value that is likely to be lost in the event of default (LIED). LIED is always specific to a given facility because it depends on the structure of the facility. PD, however, is generally associated with the borrower, the presumption being that a borrower will default on all obligations if it defaults on any. The product of PD and LIED is the expected loss (EL) on the exposure in a statistical sense. It represents an estimate of the average percentage loss rate over time on a group of loans all having the given expected loss.

The banks generally fall into two categories with regard to loss concept. First one is one-dimensional rating system, in which ratings are assigned to facilities. In such systems, ratings approximate EL. The other is the two-dimensional systems, in which the borrower's general credit worthiness (approximately PD) is appraised on one scale while the risk posed by individual exposures (approximately EL) is appraised on another; invariably the two scales have the same number of rating categories (Tracey and Carey, 1998).

In two-dimensional systems, one grade typically reflects PD and the other EL. Banks with such systems usually first determine the borrower's grade (its PD) and then set the facility grade equal to the borrower grade unless the structure of the facility is such that LIED is substantially better or worse than "normal". Implicitly, grades on the facility scale measure EL as the PD associated with the borrower grade multiplied by a standard or average LIED (see table 4.1). In this way, a two-dimensional system can promote precision and consistency in grading by separately recording a rater's judgements about PD and EL rather than mixing them together (Tracey and Carey, 1998).

At the agencies, as at many banks, the loss concepts (PD, LIED, and EL) embedded in the ratings are somewhat ambiguous. Moody's states that "*ratings are intended to serve as indicators or forecasts of the potential for credit loss because of failure to pay, a delay in payment, or partial payment*". Standard & Poor's states that its ratings are an "*opinion of the general creditworthiness of an obligator, or ... of an obligor with respect to a particular ... obligation ... based on relevant risk factors*". On balance, a close reading of Moody's and Standard & Poor's detailed descriptions of rating criteria and procedures suggests that the two agencies' ratings incorporate elements of PD and LIED but are not precisely EL measures (Tracey and Carey, 1998).

4.3.2. Administrative Grades


All banks generally maintain some sort of internal “watch” list as well as a means of identifying assets that fall into the “regulatory problem asset” categories. Watch credits are those that need special monitoring but do not fall in the regulatory problem-asset grades. Special monitoring activity is usually undertaken for watch and problem assets, such as formal quarterly reviews of status and special reports that help senior bank management monitor and react to important developments in the portfolio. However, banks may wish to trigger special monitoring for credits that are not high-risk and thus may wish to separate administrative indicators from risk measures (Treacy and Carey, 1998).

4.4. The Operating Design of Rating Systems

In essentially all cases, the human judgement exercised by experienced bank staff is central to the assignment of a rating. Banks thus design the operational flow of the rating process in ways that are aimed at promoting the accuracy and consistency of ratings while not unduly restricting the exercise of judgement. Balance between this opposing imperatives appear to be struck at each institution on the basis of cost considerations, the nature of bank’s commercial business lines, the banks’ uses of ratings, and the role of the rating system in maintaining the bank’s credit culture.

Key operating design issues in striking the balance include the organizational division of responsibility for grading (line staff or credit staff), the nature of reviews of ratings to detect errors, the organizational location of ultimate authority over grade assignments, the role external ratings and statistical models in the rating process, and the formality of the process and specificity of formal rating definitions (Treacy and Carey, 1998). Some of these issues are explained briefly in the following paragraphs.

Table 4.1 Two-Dimensional Risk Management System

Grade	Borrower Scale: Borrowers probability of default(PD) (percent) (1)	Assumed average loss on loans in the event of default (LIED) (percent) (2)	Facility scale: expected loss (EL) on loans (percent) (1x2)
1.Virtually no risk	0	 30	0
2.Low risk	.1		.03
3.Moderate risk	.3		.09
4.Average risk	1.0		.30
5.Acceptable risk	3.0		.90
6.Borderline risk	6.0		1.80
7.OAEM*	20.0		6.0
8.Substandard	60.0		18.0
9.Doubtful	100.0		30.0

*Other Assets Especially Mentioned

(Treacy and Carey, 1998)

Table 4.2. Regulatory Problem Asset Categories

Category	Regulatory definition	Recommended Specific Reserve(%)
Special Mention (OAEM)	<ul style="list-style-type: none"> - Has potential weaknesses that deserve management’s close attention. - If left uncorrected, these potential weaknesses may, at some future date, result in the deterioration of the repayment prospect for the credit. 	No recommendation
Substandard	<ul style="list-style-type: none"> - Inadequately protected by current worth/paying capacity of obligor or collateral. Well-defined weaknesses jeopardize liquidation of the debt. - Distinct possibility that bank will sustain some loss if deficiencies are not corrected. 	15
Doubtful	<ul style="list-style-type: none"> - All weaknesses inherent in substandard, and collection/liquidation in full, on basis of currently existing conditions, is highly questionable or improbable. - Specific pending factors may strengthen credit; treatment as loss deferred until exact status can be determined. 	50
Loss	<ul style="list-style-type: none"> - Uncollectible and of such little value that continuance as bankable assets is not warranted. - Credit may have recovery or salvage value, but not practical/desirable to defer writing it off even though partial recovery may be effected in future. 	100

(Treacy and Carey, 1998)

- **How the ratings are assigned:** Both assigners and reviewers of ratings follow the same basic thought process in arriving at a rating for a given exposure. The rater considers both the risks posed by the borrower and aspects of the facility's structure. In appraising the borrower, the rater gathers information about its quantitative and qualitative characteristics -by means of financial and intelligence analyses-, compares them with the standards for each grade, and then weights them in choosing a borrower grade. The comparative process often is as much one of looking across borrowers as one of looking across characteristics of different grades: That is, the rater may look for already-rated loans with characteristics close to those of the loan being rated and then set the rating to the grade already assigned to such borrowers (Treacy and Carey, 1998).
- **Factors considered while assigning the ratings:** Bank personnel base their decisions to assign a particular rating on the criteria that define each grade, which are articulated as standards for a number of specific risk factors. For example, a criterion for assignment of a grade "3" might be that the borrower's leverage ratio must be smaller than some value. Risk factors include the borrower's financial condition, size, industry, and position within the industry (financial and intelligence analysis); the reliability of the borrower's financial statements and the quality of its management; elements of transaction structure (for example, collateral); and miscellaneous other factors. The risk factors are generally the same as those considered in deciding whether to extend a loan and are similar to the factors considered by rating agencies. Banks vary somewhat in the particular factors they consider and in the weight they give each factor.

Financial statement analysis is central to appraising the likely adequacy of future cash flow and thus the ability of the borrower to service its debt. The focus of analysis is on the borrower's debt service capacity, taking account of its free cash flow, the liquidity of its balance sheet, and the firm's access to sources of finance other than the bank (risk ratios). Historical (and to a lesser extent, projected) earnings, operating cash flow, interest coverage, and leverage are typically analysed, with exact definitions of financial ratios used in the analysis varying across banks and, in some cases, across borrowers or loan types. The analysis yields an assessment of the difference between current or projected

performance and liquidity on the one hand and projected debt service obligations on the other. The larger the cushion, in general, the more favourable the rating.

As a context for financial statement analysis, the characteristics of the borrower's industry are often considered (such as cyclically, general volatility, and trends in cash flow and profitability). Indeed, the financial analysis often includes a formal comparison of the borrower's financial ratios to prevailing industry norms. Firms in declining industries are considered more risky, as are those in highly competitive industries, whereas firms with diversified lines of business are viewed as less risky (intelligence analysis). A related factor, the borrower's position in its industry, is also an important factor in determining ratings. Those borrowers with substantial market power or that are perceived to be "market leaders" in other respects are considered less risky because they are thought to be less vulnerable to competitive pressure.

One of the most important reasons that rating is usually a judgmental process is that the details of financial statement analysis vary with the borrower's other characteristics. In contrast, statistical models of default probability tend to analyse fixed sets of financial ratios and to apply fixed weights to each ratio in arriving at a default probability, perhaps with some variation in weights by industry. Subjective factors play at most a minimal role. This relative inflexibility of models leads most banks to regard their results only as generally suggestive of an appropriate rating. When internal ratings are produced primarily by models, several models may be needed for different borrowers or loan types and continual tuning of the models is likely to be required.

Raters also appraise the quality of financial information provided by the borrower. For example, raters have much more confidence in financial statements that are audited by a major accounting firm than in those that are compiled or unconsolidated or that are audited but accompanied by important qualifications. When statement quality is poor or uncertain, financial analysis may produce a distorted view of the borrower's condition, adding substantially to risk.

The borrower's country of domicile or operations is an important determinant of the rating in some cases. Especially when transfer risk or political risk is substantial, general practice seems to be that a borrower's grade may be no less risky than the grade assigned to the borrower's country by a special unit in the bank.

Such country grades can be significantly affected by the country risk grade assigned by regulators as part of an annual cycle. Ratings may also be influenced by exposure to event risks, such as litigation, environmental liability, or changes in law or national policy. A handful of considerations reflecting the structure of the transaction being rated also enter into consideration because they can affect LIED. Adequate collateral can in many cases improve the rating, particularly if that collateral is in the form of cash or easily marketed assets (Treacy and Carey, 1998).

- **Reviews and reviewers:** Reviews of ratings are threefold: (1) monitoring by those who assign the initial rating of a transaction, (2) regularly scheduled reviews of ratings for groups of exposures, and (3) occasional reviews of a business unit's rating assignments by a loan review unit. Most institutions also conduct annual or quarterly reviews of each exposure, which may be in addition to those that are part of the credit approval process at the time facilities are renewed. Ratings are also checked by banks' independent loan review units, which usually have the final authority to set grades. Owing to the operational rating definitions and procedures are embedded in bank culture rather than written down in detail, the loan review function at most institutions is critical to maintaining the discipline and consistency of the overall rating process. Loan review units usually have a role apart from inspections in maintaining rating system integrity. For example, when a relationship manager and the credit staff are unable to agree on a rating for a new loan, they will consult with the loan review unit on how to resolve the dispute. In its consultative role, the loan review staffs guides the interpretations of rating definitions and standards and, in novel situations, establishes and refines the definitions. Loan review units may be less critical to the integrity of rating systems at banks that are primarily in the business of making large corporate loans and at which all exposures are rated by a relatively small, highly independent credit staff (Treacy and Carey, 1998).

The rating process has many interlinked elements. At almost all large banks, internal rating systems rely importantly on the judgment of staff operating with relatively little written guidance. The operational definition of each grade is largely an element of credit culture that is determined and communicated by informal means. Review activities, especially those conducted by loan review units, are crucial for maintaining the culture in

that the feedback they give is critical to common understanding and discipline. Points of external comparison, such as agency ratings or results of statistical models of borrower default probability, can be helpful in maintaining the integrity of internal ratings (Treacy and Carey, 1998).

4.5. Risk Rating Systems

In general, in designing rating systems, bank management must weigh numerous considerations, including cost, efficiency of information gathering, consistency of ratings produced, staff incentives, the nature of the bank's business, and the uses to be made of Internal ratings.

There does not appear to be one "correct" rating system. Instead, "correctness" depends on how the system is used. For example, a bank that uses ratings mainly to identify deteriorating or problem loans to ensure proper monitoring may find that a rating scale with relatively few grades is adequate. In contrast, if ratings are used in computing internal profitability measures, a scale with a relatively large number of grades may be required to achieve fine distinctions of credit risk (Treacy and Carey, 1998).

As with the decision to extend credit, the rating process almost always involves the exercise of human judgment because the factors considered in assigning a rating and the weight given each factor can differ significantly across borrowers. Given the substantial role of judgment, banks must pay careful attention to the internal incentives they create and to internal rating review and control systems to avoid introducing bias.

Many banks use statistical models as an element of the rating process, but banks generally believe that the limitations of statistical models are such that properly managed judgmental rating systems deliver more accurate estimates of risk. Especially for large exposures, the benefits of such accuracy may outweigh the higher costs of judgmental systems. In contrast, statistical credit scores are often the primary basis for credit decisions for small lending exposures, such as consumer credit (Treacy and Carey, 1998).

Rating systems should be designed so that an appropriate tradeoff between effectiveness (accuracy, consistency and timeliness of ratings) and efficiency (cost of assigning the ratings with a given frequency) is reached in each lending sector. Different combinations of experience-based judgment and quantitative models are typically used in different sectors. In some sectors experience-based judgment is the most common means for assigning/updating ratings; in others, statistical scoring models are the predominant vehicles.

The four major options for risk rating system design are positioned on the figure 4.2 below:

<u>I</u>	<u>II</u>	<u>III</u>	<u>IV</u>
Pure Judgment	Template	Score sheet	Pure Model

(OWC Credit Comments, 1993)

Figure 4.2 Rating Systems Spectrum

Under Option I, the grader evaluates credits judgmentally against a set of qualitative guidelines (e.g., risk rating “B” is a credit which is “marginally acceptable”); under Option IV, a model provides the final rating without judgmental input.

The two intermediate options (II, III) combine judgment and models in different ways:

- Under Option II the final ratings are ultimately judgmental, but graders are provided with a template of quantitative benchmarks for each rating category (e.g., financial ratios or bond rating equivalents) to guide their judgment and perhaps some quantitative rules, which constrain their judgment (e.g., unless the coverage ratio is at least “X”, the rating cannot be above “BB”). In general, though, this rating process leans toward the subjective, graders can weight the various underlying factors (financial condition, industry attractiveness, management quality, etc.) judgmentally, and can generally interpret the quantitative measures provided as guidelines rather than constraints.
- Under Option III, the grader is provided with a score sheet, which combines a set of objective characteristics (e.g., financial ratios) with a set of subjectively judged characteristics (e.g., management quality) in a predetermined manner. While leaving a certain proportion of the final rating to judgment, this rating process leans toward the “pure model” end of the spectrum; the weights of the various underlying factors are explicitly set, and judgments are essentially used to alter a base evaluation formed by a model (OWC Credit Comment, 1993).

Most commercial loan rating systems are currently at or near the “pure judgment” end of the spectrum; most consumer loan rating systems are at or near the “pure model” end of the spectrum. This reflects the general perception that models make sense in those sectors where credit decision-making efficiency is critical; in sectors where effectiveness is more critical, banks have tended to rely upon judgment.

However, eight separate academic studies of commercial loan decision-making have concluded that a “pure model” approach (Option IV) outperforms a “pure judgment” approach (Option I). Models add an element of consistency to the rating process, which is lacking in human judges, particularly when a diverse set of graders is making the judgments. Other tests have shown that models can also help on other dimensions of effectiveness (e.g., timeliness). As a result, it is inclined toward rating systems that incorporate quantitative model in some form. It can be advocated that banks proceed on two parallel tracks

- * Use one of the intermediate options (II or III) as the primary rating system, in this way, some of the attributes of models as well as judgment are combined in a manner which, conceptually, captures the primary value of each.
- * Track the results of the pure model approach (option IV) as a secondary rating system, in this way, the specific value provided by allowing judgmental adjustment can be measured over time in each lending sector.

The two-track approach allows for a continually improving rating system; the primary and secondary approaches can be separately evaluated for accuracy, consistency and timeliness, and insight into potential improvements gained (e.g., adjusting the model-to-judgment balance by sector or adjusting the weights of underlying factors). The fine-tuning that this process allows will ultimately maximise the effectiveness of the rating system (OWC Credit Comment, 1993).

4.6. A Simple Example to the Risk Rating Systems

Final step in the traditional approach is to determine the loan amount and risk rating of the borrower in the light of the financial analysis and the intelligence analysis. All of the large banks have internal rating systems, which help the loan officers to manage the credit risk by means of modern approach.

Following tables show a simple example to a rating system, and the example shows how a credit manager calculates the rating of a firm from the information obtained from financial analysis and intelligence analysis.

From the table 4.3, the first risk score based on the financial analysis is calculated (in table 4.3, an example is exhibited -P1 and P2 column- and risk score calculated upon this numbers), and loan officer uses the table 4.4 and equation 4.1 as basis for the both of the calculation.

Table 4.3 Risk Point Based on Financial Analysis

Financial Values and Ratios*		Good	Medium	Poor	P1	P2
1	Current Assets	↑	-	↓	3	2
2	Short-term debts to banks	↓	-	↑	2	2
3	Total Short-term debts	↓	-	↑	2	2
4	Total Assets(%)**	>100(%)	50-100(%)	>50(%)	3	3
5	Owners' equity**	>100(%)	50-100(%)	>50(%)	1	1
6	Net Sales**	>inflation	=inflation	<inflation	3	3
7	Net Working Capital	↑	-	↓	2	2
8	Current ratio	>1,5	1-1,5	<1	2	2
9	Inventory turnover ratio(%)	↑	-	↓	3	3
10	Total liabilities/Total assets(%)	<50(%)	50-70	>70(%)	2	2
11	Financial expenses	↓	-	↑	2	2
12	Operating income	↑	-	↓	3	3
13	Period profit-loss	↑	-	↓	2	2
14	Net income/Net sales(%)	>15(%)	10-14(%)	<9(%)	1	1
TOTAL RISK POINT***					31	30

(Usta and Tacuman, 1997)

*All ratios and values should be evaluated according to the previous years (horizontal analysis).

**These values are analysed by means of trend percentage analysis.

***If current ratio>inflation, 3 point is added to risk point, if current ratio<inflation, 3 point is deducted from risk point. If the firm has the negative net income or has net loss, 2 point is deducted from risk point.

$$\text{Risk score} = \frac{\text{Total risk point}}{\text{Number of values and ratios}} \times 100 \quad (4.1)$$

The first risk score is **217** $((30.5 \div 14) * 100)$ and the first risk rating -according to the risk score- is A. From the table 4.5, second risk score based on the intelligence analysis can be found as **250** $((50 \div 20) * 100)$ and the second risk rating based on the risk score is A.

$$\text{Overall risk score} = (\text{first risk score} \times 0.6) + (\text{second risk score} \times 0.4) \quad (4.2)$$

As a result, the overall risk score and rating of a firm can be calculated from the first and second scores according to the equations 4.2.

The overall risk score of the firm is 230 $([217 * 0.634 + 250 * 0.4])$ and the overall risk rating of the firm is A.

Table 4.4 Risk Ratings Based on Risk Scores

<u>Risk Score</u>	<u>Risk Rating</u>
100-135	BBB
136-165	BB
166-206	B
207-250	A
251-278	AA
279-300	AAA

(Usta and Tacuman, 1997)

The questions in table 4.5, the values and ratios in table 4.3 and weight of risk scores in equation 4.2 can vary from financial institution to financial institution according to their experience or subjective assessments of the conditions. It is important to calculate the risk ratings of the firms for the quantification of the risk and for the sake of forming the transition matrix(*) from the risk rating data. The transition matrix can be only formed by collecting risk rating data for many years. These statistical studies will be very useful to manage the credit risk.

(*) A square table of probabilities which summarise the likelihood that a credit rating will migrate from its current credit rating today to any possible credit rating -or perhaps default- in one period.

Table 4.5 Risk Point Based on Intelligence Analysis

Questions	3	2	1	P
1. Production technology*	good	medium	poor	3
2. Dependence to the other producers*	low	medium	high	3
3. inventory level*	low	medium	high	2
4. Dependence to the foreign n suppliers*	low	medium	high	2
5. Fluctuations in the raw material prices*	low	medium	high	2
6. Demand to the product	good	medium	poor	3
7. Fluctuations in the economic conditions	low	medium	high	2
8. Market share	good	medium	poor	3
9. Financial and accounting system	good	medium	poor	3
10. Ability of collecting the draft, cheque, etc.	good	medium	poor	3
11. Commitment to the obligations	good	medium	poor	3
12. Personal lives of the partners, managers, etc.	good	medium	poor	2
13. Job experience	good	medium	poor	3
14. Appropriateness of the location of the firm	good	medium	poor	3
15. Relations among the partners and managers	good	medium	poor	3
16. Quality of the employees	good	medium	poor	2
17. Relations among the employees	good	medium	poor	2
18. Firm’s industry position	good	medium	poor	2
19. Ability of a back the credits	high	medium	low	2
20. Ability of converting the collaterals to cash	high	medium	low	2
TOTAL RISK POINT				50

*These questions are only for the manufacturing firms.

(Usta and Tacuman, 1997)

4.7. Measuring Loss Characteristics by Grade

Consistent and accurate rating assignments and reliable quantitative estimates of the risk associated with each internal grade are useful in a bank’s efforts to analyse risk posture, establish its appetite for risk, and evaluate the effectiveness of its risk rating criteria. At most banks, however, the primary demands for quantitative information about PD, LIED, and EL have come from those involved in the loan loss reserve process and

from credit modelling groups (those building and implementing quantitative models of portfolio risk, capital allocation, profitability, and pricing). Internal ratings are key inputs into such processes.

If internal ratings are to be accurate and consistent in terms of the system's loss concepts (that is, PD, LIED, or EL), different assets posing a similar level of risk should receive the same grade. Such quantities are not observable *ex ante*, however, and thus rating systems rely on criteria that are thought to predict loss. Accuracy and consistency require that rating criteria be adjusted as necessary to ensure that exposures posing similar risk are grouped together (Treacy and Carey, 1998).

Because little information is available internally, many banks have estimated the quantitative loss characteristics of their ratings by using the extensive data available on the loss performance of publicly issued bonds. Rating agencies and others frequently publish studies covering many years of bond default and loss experience by grade, and publicly available databases of bond issuer characteristics make it possible to relate loss experience to potential rating criteria.

To use data on bond loss experience, a bank must develop or assume some correspondence between agency ratings and its own internal grades. The basis of such mappings is threefold (1) The internal grades assigned to borrowers who have also issued publicly rated bonds; (2) analysis of the "typical" financial characteristics of bank borrowers in each internal grade *vis-à-vis* the characteristics of the firms with bonds in each agency grade; and (3) subjective analysis.

Both banks and rating agencies assign ratings based on criteria that are predictive of a borrower's probability of default (PD) or a loan's expected loss (EL). However, because no mechanical formula exists that converts criteria into values of PD or EL for each grade, such values must be obtained from historical loss experience. Banks rarely have databases of such experience, but the major rating agencies do. A mapping of internal grades to agency grades permits a bank to use statistics from the agencies' bond default studies to assign values of PD to each of its internal grades (Treacy and Carey, 1998). Four problems can cause a mapping to lead to a materially inaccurate estimate of PD for internal grades:

- A bank's rating system may place loans with widely varying levels of PD into the same grade and similar levels of PD into different grades. In this case, grades bear little relation to PD values and thus mapping will not provide good estimates of PD.
- Default rates on publicly issued bonds may differ systematically from loan default rates.
- The mapping exercise may simply associate the wrong agency grades with internal grades.
- The implications of differences between banks' point-in-time and agency through-the-cycle rating philosophies may not be taken into account.

Because major agencies rate borrowers with the expectation that the rating will be stable through normal economic and industry cycles, only those borrowers that perform much worse than expected during a cyclical downturn will be downgraded (will "migrate" to riskier grades). In contrast, rating systems that focus on the borrower's current condition (virtually all bank systems) are likely to feature much more migration as cycles progress but, in principle, should exhibit somewhat less cyclical variation in default rates for each individual grade. Obtaining reasonably accurate mappings is mainly matter of paying attention to the stage of the cycle at which the mapping is being done and of using historical average PD values from either good-experience or bad-experience years as appropriate (Treacy and Carey, 1998).

For risk measurement purposes, the importance of the credit rating process derives from the fact that, within most credit risk models, the internal credit risk grade is treated as a "sufficient statistic" for summarising a facility's probability of defaulting within the relevant planning horizon. This translation is often accomplished through a two-step process involving, first, the construction of a concordance table relating the bank's internal credit grades to some external rating standard, usually S & P's or Moody's ratings for corporate bonds. A grade-1 loan may be deemed roughly equivalent to an S&P bond rating from AA to AAA, a grade-2 loan equivalent to a bond rating of single-A, and so on. Given this concordance, the probability of a customer defaulting on its obligations (or migrating to another credit risk grade) is usually inferred from (a) published tables of the historical default frequencies of similarly-rated corporate bonds, (b) any available internal data on the historical default rates of loans originated by the bank itself, and/or (c) consultants' knowledge of the default rates experienced by other banks.

Internal credit ratings play an important role not only as a “first step” in the credit risk measurement process but also as an important stand-alone risk management tool. Credit ratings within the large corporate businesses are a basis for regular risk reports to senior management and boards of directors. Credit ratings are also the basis for a continuous loan review process, under which large corporate credits generally are reviewed and regarded at least annually in order to focus attention on deteriorating credits well before they become “criticised” by examiners or external auditors.

Some banks attempt to attenuate this problem by adjusting an instrument's credit rating for its maturity (tantamount to adjusting its probability of defaulting within the one-year planning horizon). That is, a longer-term loan would be assigned a lower credit rating (higher probability of default) than a short-term credit to the same customer. For example, key parameters other than default probabilities, such as correlations among loan defaults, generally are *not* similarly adjusted for maturity. As a consequence, it is difficult to assess the overall impact and effectiveness of such adjustments.

CONCLUSION

Credit risk is important and inevitable for the banks and the other financial institutions.

A bank or a financial institution can implement a rigorous program to manage its portfolio for maximum return while maintaining risk at the prescribed level and managing risk exposures. CreditMetrics and CreditRisk+ models are given in this thesis as the two of modern credit risk management models to provide the means by which a bank or a financial institution manage its credit or default risks.

In Turkey also credit risk management framework should be implemented due to the inevitable globalization process. It is concluded that all banks in Turkey have their database for the needed data. From the view of the financial institutions, only thing is to do is that to initiate and speed up the studies on these models. From the view of the regulators, it must be set up the minimum requirements, needed acts, rules or regulations and must be prepared the required environment to develop these models.

It is recommended that, prospective researchers, work out the parameters of the probability of default, default correlation, and default volatility. Furthermore, it can be figured out which distribution is best expressing the credit/default events or how the parameters are sensitive to the distributional assumptions, the relation between the economic variables and the model parameters, the relation between the economic conditions and the credit events.

REFERENCES

1. Basle Committee on Banking Supervision, 1999a, "*Credit Risk Modelling : Current Practices and Applications*", Basle. Available at site <http://www.bis.org/publ/bcbs49.htm>
2. Basle Committee on Banking Supervision, 1999b, "*Principles for the Management Of Credit Risk*", Basle. Available at site <http://www.bis.org/publ/bcbs54.htm>
3. Basle Committee on Banking Supervision, 1999c, "*Best Practices for Credit Risk Disclosure*", Basle. Available at site <http://www.bis.org/publ/bcbs53.htm>
4. Basle Committee on Banking Supervision, 1999d, "*A New Capital Adequacy Framework*", Basle. Available at site <http://www.bis.org/publ/bcbs50.htm>
5. Cormac, B., *Mastering Value at Risk*, Financial Times Pitman Publishing, London, 1999
6. Credit Suisse Financial Products, 1997, "*CreditRisk⁺: A Credit Risk Management Framework*", London. Available at site <http://www.csfp.csh.com/csfpod/html/csfpJO.htm>
7. Garrison, R.H. and Noreen, E.W., *Managerial Accounting*, 8th Edition, McGraw-Hill, New York, 1997.
8. Gordy, M.B., 1998, "*A Comparative Anatomy of Credit Risk Models*", Federal Reserve Board, Washington D.C. Available at site <http://www.federalreserve.gov>
9. Gupton, G.M., Finger, C.C. and Bhatia, M., *CreditMetricsTM - Technical. Document*, Morgan Guaranty Trust Co., New York, 1997. <http://www.riskmetrics.com>
10. Jones, D. and Mingo, J., 1998, "Industry Practices in Credit Risk Modelling and Internal Capital Allocations : Implications for a Models-Based Regulatory Capital Standard", *Federal Reserve Bank of New York Economy Policy Review*, October.
11. Jorion, P., *Value at Risk: The New Benchmark for Controlling Market Risk*, McGraw-Hill, New York, 1997.

12. *Regulation on Banks' Internal Control and Risk Measurement Systems, Issued by the Banking Regulation and Supervision Board, Published in the Official Gazette, issue no. 24312 on 08 February 2001*
13. *Regulation on Measurement and Assessment of Capital Adequacy of Banks, Issued by the Banking Regulation and Supervision Board, Published in the first supplementary issue of the Official Gazette no. 24314 of 10.02.2001*
14. Skora, R., 1998, "*Credit Risk Management Models*", Skora&Company, New York, <http://www.skora.com>
15. Treacy, W.F. and Carey, M.S., 1998, "Credit Risk Rating at Large U.S. Banks", *Federal Reserve Bulletin*, November, pp.897-921. Available at site <http://www.federalreserve.gov>
16. Treacy, W., 1998, "Sound Credit Risk Management and the Use of Internal Credit Risk Ratings at Large Banking Organizations", *Federal Reserve Supervision and Regulation Letter SR 98-25*, September 21. Available at site <http://www.federalreserve.gov/boarddocs/srletters/1998/sr9825.htm>.
17. Usta, M. and Tacuman, D.K., *Istihbarat ve Mali Analiz*, 2nci Baski, Pamukbank Egitim Yayınları, Istanbul, 1997.

CV

Date of Birth : 01.01.1964

Birth Place : Sorgun/YOZGAT

Marital Status : Married

Education : 1978-1982 Sorgun Lisesi, Sorgun/YOZGAT
1982-1987 Gazi Universitesi, İ.İ.B.F., İktisat Bölümü

Institutions : 1998-2001 Etibank/Esbank
1991-1998 Türkbank
1998-1991 Halkbank