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ABSTRACT

Theories, methods, and tools to measure and control market risks have been developed, discussed, and applied. On the other hand, tools and frameworks of credit risk management have not been integrated with a market risk based ALM framework, although taking appropriate credit risk is one of the major sources of profit for institutional investors. This paper first applies statistical methods to historical default data. The result indicates strong relationship between credit risk and default probabilities. The writers of the paper investigate a method to integrate quantified credit risk with a market risk based ALM framework. Parameters to be used are expected default probabilities of credit risk clustered asset classes and variances of these. The use of these parameters makes it possible to manage credit risk and market risk simultaneously. The paper proposed a credit risk integrated ALM framework consisting of four parts: a credit risk adjusted return analysis model, an asset allocation optimization model, a market risk sensitivity analysis model, and a credit risk exposure control standard.

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Integration of Credit Risk with Market Risk in Asset Liability Management

September 30, 1995

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Abstract

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The paper proposes a credit risk integrated ALM framework consisting of four parts: a credit risk adjusted return analysis model, an asset allocation optimization model, a market risk sensitivity analysis model, and a credit risk exposure control standard.

1. Introduction

Today, the most advanced financial institutions are building ALM frameworks. Compared to older attitudes towards investments, this trend is a great step toward controlling various risks. However, most of these frameworks seem to be constructed with the intention of controlling only the market risk.

The biggest flaw of a market risk controlling ALM framework is that it lacks any aspects of credit risk taking and controlling. Credit risk may seriously affect asset liability management because it causes uncertainty of cash flows due to possible defaults of issuers/borrowers. That is one problem of using a market risk controlling ALM framework. The other problem is ignorance of the default probability, which may result in the irrationality in investments. For example, if an annualized expected default probability of an issuer/borrower is larger than the market yield spread over a default free yield such as a treasury yield, and if investors are risk avertors, these investors would be better off investing in the treasury market. However, investors often invest in issuers/borrowers of worse credit risk without requiring sufficient risk premium over default free yields just to enjoy nominally higher returns than those of default free investments.

For a long time, the source providing the major part of profit for financial institutions has been credit risk taking. For this, risk tolerance has been required of them. In the good old days, their focus was on this issue, but without quantitative view point, and they dealt with this problem with conservatism. Then new waves came along: deregulation, securitization, and severe fluctuation of interest rates. Financial institutions started to focus on market risk taking technology, leaving credit risk taking ability behind. In this paper, we reveal this imbalance in financial institutions' thinking and practice, and propose an asset liability management framework that considers both market risk and credit risk.

2. Default Study

One reason that prevents the credit risk controlling aspect from being included in the currently existing ALM frameworks is low availability of a well-organized default data set with credit risk information. Rating agencies publish default studies for better credit entities, but the rating coverage does not reach to the corporate loan credit risk level to which most of the loans in portfolios of financial institutions belong. It is possible that some financial institutions accumulate credit risk related data for internal use, but usually they do not construct a database for analytical use. Without having reliable default probabilities, it is difficult to estimate appropriate yield spreads over default free yields. Without having an appropriate level of yield spreads to require, financial institutions cannot control credit risk quantitatively.

The present writers have used well-organized default data with indexed credit risk information from Teikoku Data Bank, a credit risk rating agency in Japan. We have analyzed the data set and calculate historical default probabilities and variances. The database covers more than 700,000 data for 11 years. Based on the financial data of each company, Teikoku Data Bank publishes its credit condition points with 100 as "full mark" and 1 as the worst mark. Some companies covered by Teikoku Data Bank are also rated by rating agencies, and there are clear relationship between ratings by rating agencies and credit condition points. Roughly speaking, AAA rated companies get 91 to 95 points, AA rated companies get 86 to 90 credit condition points, and A rated companies get 81 to 85 points. These points are given and published at least once a year. Data series of the data set are credit condition points of each company and time of bankruptcy. We dealt bankruptcy as the same meaning as default in the new ALM framework, although there are slight differences.

First, we divide the companies into 21 clusters by their credit condition points. Then, based on the cluster at the beginning of the observation period, we calculate cumulative default rates from one year period to 11 year period. In the analysis, we do not deal with clusters with 30 or lower credit condition points as sample sizes are relatively small. Table 2-1 and Figure 2-1 show the results. Default rates of clustered company groups in good credit condition are lower than those of companies in bad credit condition.

Table 2-1 and Figure 2-1 also show the standard deviations of credit risk clusters calculated from the historical default rates. When using historical default rates as the expected default probabilities, it is safer to have a buffer as the data period may not long enough. We use a 95% one-sided confidence limit to cover the possible shortfall of a relatively short data period. Please refer to Figure 2-2.

3. Credit-risk Adjusted Return Analysis Model

With expected default probabilities derived from historical data, we propose a model to measure performance of individual investments against markets, mainly bonds and loans. The object of this evaluation process in the ALM framework is to alter investment attitudes so that the appropriate risk premium would be earned from credit risk taking.

The evaluation model requires three sets of data of an individual investment: expected cash flows from investment, expected default probability of an issuer/borrower, and expected residual value of the investment in the event of default. It also requires a default free yield curve and a market yield spread of the credit risk cluster over default free yield.

The main part of the evaluation is estimation of a market average yield (MAY) for similar credit risk taking. A MAY is a summation of the default free yield at the comparable term and the yield spread of the comparable credit risk.

$MAY = r_f + YS_m$

where: r_f: Default Free Yield

YS_m: Market Yield Spread

Suppose investors are risk avertors, they would prefer the investment with more certain cash flows when comparing two alternatives with the same expected returns. It means that, even though they would enjoy the same yield after deduction of the expected loss, they prefer a default free investment. If the possible default affects the cash flows, investors require higher returns on higher credit risk taking investment even after adjustment of the expected default loss. This tendency is clearly observed in the Euro Yen bond secondary market. First, we calculate a JGB zero yield curve as a default free investment. Based on the JGB zero yield, we calculate a market average yield curve of each credit risk level from AAA to A. In the calculation, we assume that there are no term structures on yield spreads. (Please refer to Figure 3-1 for results as of March 31, 1994.) It is clear that a wider yield spread is required by market participants for the investments with larger credit risk. It is reasonable to estimate that the yield spread required by investors includes the expected default loss equivalent yield (EDLEY). The results show that the yield spread is wider than the EDLEY. We regard the residual of the yield spread after deduction of the EDLEY as the compensation equivalent yield for credit risk taking (CEY). If investors are risk avertors, they require compensation for uncertain cash flows. This requirement depends on degree of uncertainty, or in other words, probability of default.

The CEY may include other factors such as the liquidity premium within the same asset class, e.g. the liquidity premium of an AAA rated bond versus that of an AA rated bond. However, we include these factors in the CEY together with the pure required compensation equivalent yield for credit risk taking. Our belief is that it is reasonable to estimate that spreads that represent other factors are also wider for higher credit risk taking.

$YS_E = EDLEY + CEY$

where: YS_E: Expected Yield Spread

$EDLEY$: Expected Default Loss Equivalent Yield

CEY: Compensation Equivalent Yield for Credit Risk Taking

If an investment is made at a credit level where a market yield spread is observable, calculation of a MAY is quite simple. Please refer to Figure 3-2 for quantification process. In the estimation of EDLEYs for bonds, we used default data from Teikoku Data Bank by analyzing relationship between credit rating by rating agencies and credit condition points by Teikoku Data Bank.

Relatively higher credit risk taking investments such as corporate loans usually do not have liquid secondary market. In the evaluation of investments in this credit risk range, we need additional assumptions on non-observable market yield spreads. We estimate the yield spread for each credit risk cluster based on the observed yield spreads for lower credit risk. Please refer to Figure 3-3. Rules governing the estimation are: 1) the yield spreads have to be wider for higher credit risk, and 2) CEYs have to be wider for the higher credit risk. These rules are consistent with the concept of the model. For example, borrowers with 56 to 65 credit condition points have certain EDLEY. On the other hand, CEY would be estimated for the credit level so that CEY is wider than that of better credit. Adding EDLEY and CEY gives estimated yield spread.

The other difficulty is the quantification of the liquidity premium. We also make the following assumption as there are no reasonable and directly observable liquidity premiums. If the capital markets are efficient, fund raisers have to pay the same cost whether they raise money in the bond market or in the corporate loan market. In reality, the annualized funding cost difference is about 15 basis points for BBB or better rated companies. We double the liquidity premium for companies with a credit risk profile below this level.

Based on all the assumptions and estimations above, we arrive at the estimated MAY for any credit risk cluster. We also have the investment yields to evaluate. The evaluation of an individual investment process is a calculation of "theoretical value". In the cash flow generation, we differentiate two characteristics of credit risk: event of default and residual value. Residual value is determined by recovery rate and collateral coverage. Please refer to Figure 3-4. The example of the non-collateralized investment shows that the residual value in the event of default is 20%. The example of the partially collateralized investment shows that the residual value is 68%. Cash flows are probability weighted average of nominal cash flows and expected cash flows when default occurs. Several estimations are possible for cash flows when default occurs, but the easiest way is to assume that the default occurs in the middle of the investment period, and at that time investors receive residual value. Figure 3-5 indicates cash flow generation and yield spread calculation process for collateralized investments. Discounting the probability weighted average of cash flows with MAYs of corresponding terms in the corresponding credit risk cluster, investors can calculate a theoretical value of the investment.

Figure 3-6-1 and Figure 3-6-2 are case studies of MAY based evaluations of individual investments. For comparison purpose, we convert yield of each investment. Case 1 and 3 are evaluated as poor investments because their converted yields do not exceed MAYs. On the contrary, case 2 and 4 are evaluated as rich investments. Figure 3-7-1 to Figure 3-7-5 are examples of macro level evaluations of investments by asset categories. The result implies that in the Japanese loan market, financial institutions do not require relative premium on riskier investments against safer investments.

4. Credit-risk Allocation Optimizing Model

In the previous section, we proposed performance measurement based on appropriateness of yield for credit risk taking. In this section, we would like to introduce an appropriate method of credit risk taking as a portfolio.

To model optimal allocation of credit risks in the ALM framework, we expand Markowitz's mean-variance model. The first expansion is consideration of the liability cost. In the asset liability management, objective function is minimizing a net return rate (asset return minus liability cost) variance under certain expected net return rate level instead of minimizing return variance of a portfolio. We subtract the historical cost data from the historical return data of each asset to estimate expected net return rates, and their variance and covariance.

The other dimension of expansion of the traditional model is integration of variance caused by expected defaults with the traditional normal distribution. The traditional model assumes a normal distribution of returns with only one peak. The assumption here is that there is no default risk, or fluctuation of cash flows caused by the event of default is included in the one-peak distribution. However, fluctuation of cash flows occurs at a certain probability. Investors have to assume a two-peak distribution of returns of a diversified portfolio which consists of investments with similar credit risk profile: one peak is at the nominal expected return and the other is at the expected default probability. Please refer to Figure 4-1. After consideration of default risk, real return-risk profile would be different from nominal one. Please refer to Figure 4-2. With the two-peak distribution concept reflected in the expansion of Markowitz's mean-variance model, the optimization problem would be written as follows:

Minimize: $$\sigma^2_{R_p} = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j \sigma^2_{R_i R_j} + \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j \sigma^2_{D_i D_j} + 2\sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j \sigma^2_{R_i D_j}$$

s.t.: $R_p = \sum_{i=1}^{N} x_i R_i - \sum_{i=1}^{N} x_i D_i$

where: R_p: Expected net return rate of portfolio (= Asset return - Liability cost)

R_i: Expected net return rate of *i*th credit-risk clustered sub-portfolio

D_i: Expected default probability of *i*th sub-portfolio

x_i: Weight of *i*th sub-portfolio

$\sigma^2_{R_p}$: Expected net return rate variance of portfolio

$\sigma^2_{R_iR_j}$: Expected net return rate covariance of *i*th sub-portfolio and *j*th sub-portfolio

$\sigma^2_{D_iD_j}$: Expected default rate covariance of *i*th sub-portfolio and *j*th sub-portfolio

$\sigma^2_{R_iD_j}$: Covariance of expected net return rate of *i*th sub-portfolio and expected default rate of *j*th sub-portfolio

Minimization of the portfolio net return rate variance gives us the optimal credit risk allocation after consideration of the cash flow fluctuation due to expected defaults. As seen in the formulas above, the expanded model requires more parameters than the traditional model. However, it gives us a better idea of credit risk allocation in the portfolio.

Using the results of the default study and the evaluation of the real investment data by the credit risk adjusted return analysis model, we calculate an example efficient frontier of the credit risk allocation. Figure 4-3 is the result based on a scenario that an investor is able to enjoy appropriate yields for credit risk taking. Figure 4-4 is the result based on a scenario that investors originate loans at lower yields for higher credit risk taking and at higher yields for lower credit risk taking compared to Figure 4-3. The results indicate that if financial institutions have poorer investment performance at some credit risk level, the efficient frontier shifts to right.

In the selection of portfolio on the efficient frontier, degree of risk aversion of a financial institution is the determinant. However, degree of risk aversion is not observable easily. We propose a new approach to the portfolio selecting problem: an introduction of a "burst probability" concept. If a financial institution knows mean and variance of expected net return rate and if there are required net return rate, the institution can estimate a probability of events that the required net return rate is not satisfied. We define such event as "burst." Different asset allocations on the efficient frontier give different burst probabilities. Portfolio selection would be made at the burst probability minimized point. Figure 4-5-1 and Figure 4-5-2 indicate examples.

5. Credit-risk Exposure Control Standard

In the expansion of the classical Markowitz's mean-variance model, we introduce the concepts of the cost and the default probability distribution. The assumption we make there is that the credit risk clustered sub-portfolio is well diversified. However, it is impossible to construct a portfolio with a definite number of small investments. Even if one can construct a portfolio with an almost definite number of small investments, the transaction/maintenance costs alter the mean-variance profile of the investment. On the other hand, if one cannot diversify the sub-portfolio, variance of the cash flow due to expected defaults would be higher.

For practical use of the proposed ALM framework, we have to set a standard for diversification of non-systematic credit risk to have virtually the same risk-return profile as the ideally diversified portfolio with a definite number of investments. The concept of the standard is to diversify the portfolio by investing in a certain number of companies equally so that the loss from default would not exceed the gain from credit risk taking. Please refer to Figure 5-1. In order to meet the object of the standard, what investors have to control is the probability of the event that the loss from default would exceed the gain from credit risk taking.

In the standard, we assume that default occurs independently and the default probability will not change over time. It depends on the investors' decision that at what level of the probability of the event that the loss from the default would exceed the return from the yield spread should be used.

Assuming investment in a single credit risk level at an equal weight diversification, gain from credit risk taking is:

$$G_P = FV \times YS \times (N_P - N_D)$$

where: G_P: Expected gain of portfolio before loss from default

FV: Face value of each investment

YS: Yield spread at portfolio credit level

N_P: Number of companies in portfolio

N_D: Number of companies expected to default in portfolio

While loss from default is:

$$L_P = FV \times N_D$$

where: L_P: Expected loss from default

To fit the concept of the standard, expected gain from credit risk taking has to be equal to or greater than expected loss from default.

$$G_P \geq L_P$$

From formulas above, we get minimum number of companies to be invested in a portfolio:

$$FV \times YS \times (N_P - N_D) = FV \times N_D$$

$$YS \times (N_P - N_D) = N_D$$

$$N_P = N_D \times \left(\frac{1}{YS} + 1 \right)$$

If a yield spread is 1% and number of companies expected to default is one, we get 101 as the minimum number of companies to be included in a portfolio for diversification. If we suppose an investor wants to keep the probability of the event that gain from credit risk taking would not cover loss from default less than 0.1%, we have to investigate whether the probability of having two or more defaults simultaneously is less than 0.1% or larger.

$$P_{N_D \geq 2} = \sum_{y=2}^{N_P} \binom{N_P}{y} p^y (1-p)^{N_P - y}$$

where: $P_{N_D \geq 2}$: Probability of having two or more defaults simultaneously

p: Expected default probability of credit risk clusters

If the default probability is 0.04%, the probability of having two or more defaults in the portfolio of 101 companies is 0.079% as seen in Figure 5-2, which is small enough to meet the requirement of the investor.

Now we look at another example. A portfolio is expected to have an annual default probability of 0.08% and a yield spread of 1.2%. The number of companies for diversification to cover the expected loss of one company in the portfolio is 84. However, unlike the previous example, the probability of having two or more defaults in the portfolio simultaneously is 0.214%. This means that the diversification is not enough. Now we recalculate number of companies for diversification assuming two defaults in the portfolio. The number of companies required would be 169. The probability of having three or more defaults is 0.037%, and the 0.1% requirement is satisfied.

Based on the number of companies for diversification, we arrive at the standard of individual credit risk exposure. The limit of credit risk exposure to an entity is calculated by dividing total size of portfolio by number of companies in each credit risk cluster. The limitation of individual credit risk exposure gives enough diversification in the portfolio.

6. Interest Rate Sensitivity Analysis Model

Roughly speaking, there are two types of ALM framework. One is a scenario approach type framework and the other is a market risk sensitivity type framework. A typical scenario approach framework usually requires several scenarios such as the most probable, unfavorable and favorable scenarios. Outputs are usually accounting profits from the asset and liability portfolio. This framework is quite old-fashioned, and from a financial view point, it is not very meaningful. It usually shows short term accounting profits, but they will not give financial institutions real information about business. This approach requires scenarios of market parameters, and it means that financial institutions have to bet on forecasts. It also lacks the ability to price option profiles in both assets and liabilities. The only merit of this approach is that it is easy for management to understand.

The second type of framework is better for market risk control. There are several models, but the basic concepts are the same. First, it generates yield curves for cash flow discount using option paths generation, Monte Carlo simulation, and other methods. Second, it generates future cash flows based on the yield curves. Third, it discounts cash flows, and calculates probability weighted average present value of assets and liabilities, then calculates surplus. It repeats these three steps for upward/downward shifted yield curves, and checks whether an investor is taking appropriate market risk (i.e. duration). Compared to the previous one, this ALM approach is better from financial view point, but the problem here is again ignorance of effects of credit risk taking in the asset and liability portfolio.

For management purposes, both the present value and the market risk sensitivity profile of the surplus are expected as outputs from an ALM framework. Surplus level is important because it indicates the profitability of the business. If the surplus is negative, there might be two factors: liability cost is too expensive or asset return is too low compared to the current market. In this sense, credit risk consideration is critical as the "real" surplus may be lower because of bad credit profile of the asset portfolio.

Credit risk also affects the sensitivity profile, though not dramatically. In the default consideration, we subtract expected default loss from the nominal cash flows. As shifts of a yield curve have a direct effect on the discount rate, deduction of the expected default loss is likely to alter interest rate sensitivity (i.e. duration and convexity).

In our framework, we discount future cash flows after deduction of expected loss with the default free yield. The result gives us the present value of both assets and liabilities, not the theoretical values investors calculate in the credit risk adjusted return analysis model. The rationality of using two different standards for pricing assets and liabilities is that we are assuming going concern business. Present value based surplus calculation is justified with the reason that gain from compensation equivalent yield would be earned even after consideration of possible defaults. On the other hand, theoretical value based performance measurement is justified because it is clearly irrational to allow worse performance than other market participants.

7. Application and further discussions

In this paper, we propose and explain each part of the new ALM framework. In this section, we would like to present an example to integrate the parts in the real application of the framework. We also note issues to be solved.

The first step of integration is estimation of default probabilities. In this step, investors have to pick a systematic method of measuring borrowers/issuers' credit risk that covers all possible investments. Availability of historical default data based on the method is the key issue. Then, they have to estimate default probabilities and the other parameters of each credit risk cluster based on historical data to be used in the ALM framework.

The second step is to decide target yields of investments based on credit risk. MAYs are used as investment targets, and they are estimated from market yield spreads and estimated default probabilities. Based on yield spreads derived from MAYs, desirable asset/credit risk allocation are calculated. Maximum exposure to one entity in each credit risk cluster is also set.

Having all the guidelines, i.e. target yields, maximum exposure, and credit risk based asset allocation, financial institutions start managing their portfolios. Lower cost of liability, better performance in investments, and higher credit risk taking push surplus level upward on the present value basis. Throughout the investment period, financial institutions have to watch the current level and the market risk sensitivity of the surplus for business decision making.

When financial institutions need to change market risk sensitivity profile, on-balance or off-balance adjustments have to be made.

The last step is the performance measurement of investments. Each investment's performance is examined against MAY. If performance of some credit risk clusters is consistently good or bad, some reasons might be: MAY estimates are too high, or the financial institutions' ability of to beat markets is poor in that credit risk range. If the latter, the financial institutions have to re-calculate credit risk exposure standard and credit risk allocation. For a better performance credit risk cluster, larger exposure would be allocated both at the individual level and at the cluster level. For a poor performance credit risk level, completely the opposite control is required. In some cases, financial institutions have to re-design liabilities and/or business itself.

In the application of the model, there are several issues to be solved.

1) Accuracy and detail in the default study

As we discussed above, accuracy of default study is required in the framework. At the same time, more detailed study is preferable such as default probabilities by sector, auto-correlation, correlation of default probability and return, and so on.

2) Market risk control

While it is not the main issue in this paper, market risk control is always one of the main issues in the ALM framework. Accuracy in the pricing, addition of market factors, speed of pricing, and other issues have to be solved. Correlation of market factors and default probabilities, if any, have to be also considered in the framework.

3) Observation of liquidity premium

In this paper, we have assumed that the liquidity premium difference between different types of investments is equal to the issue cost difference. However, if market liquidity premium is observable through the secondary markets, the assumption will have to be re-examined.

Table 2-1 Means and Standard Deviations of Cumulative Default Probabilities

Credit Condition	Means			Standard Deviations		
Points	1yr	3yrs	5yrs	1yr	3yrs	5yrs
96 - 100	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
⋮	⋮	⋮	⋮	⋮	⋮	⋮
71 - 75	0.02%	0.07%	0.14%	0.01%	0.06%	0.11%
⋮	⋮	⋮	⋮	⋮	⋮	⋮
46 - 50	1.46%	3.84%	5.62%	0.73%	1.65%	1.82%

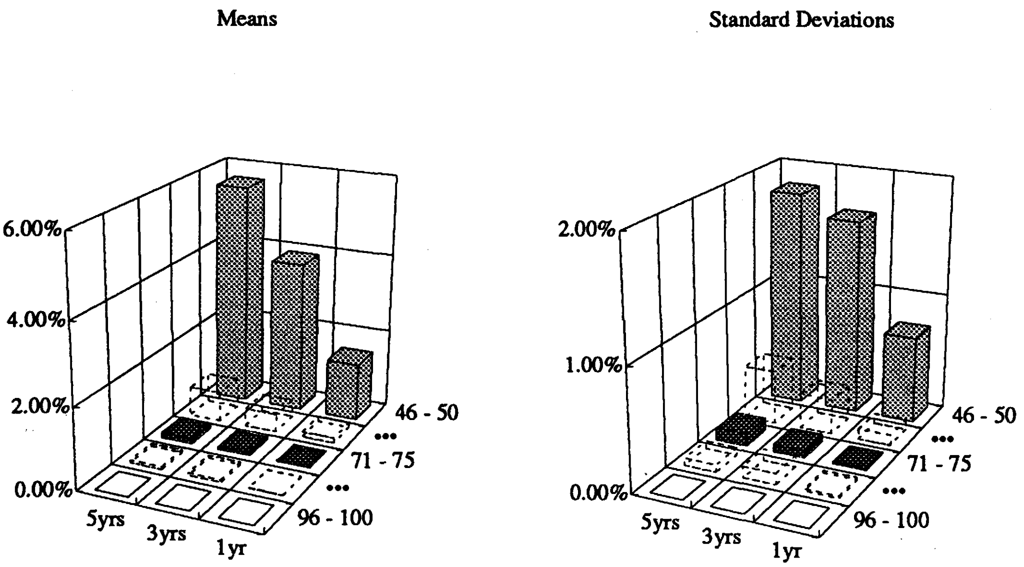


Figure 2-1 Means and Standard Deviations of Cumulative Default Probabilities

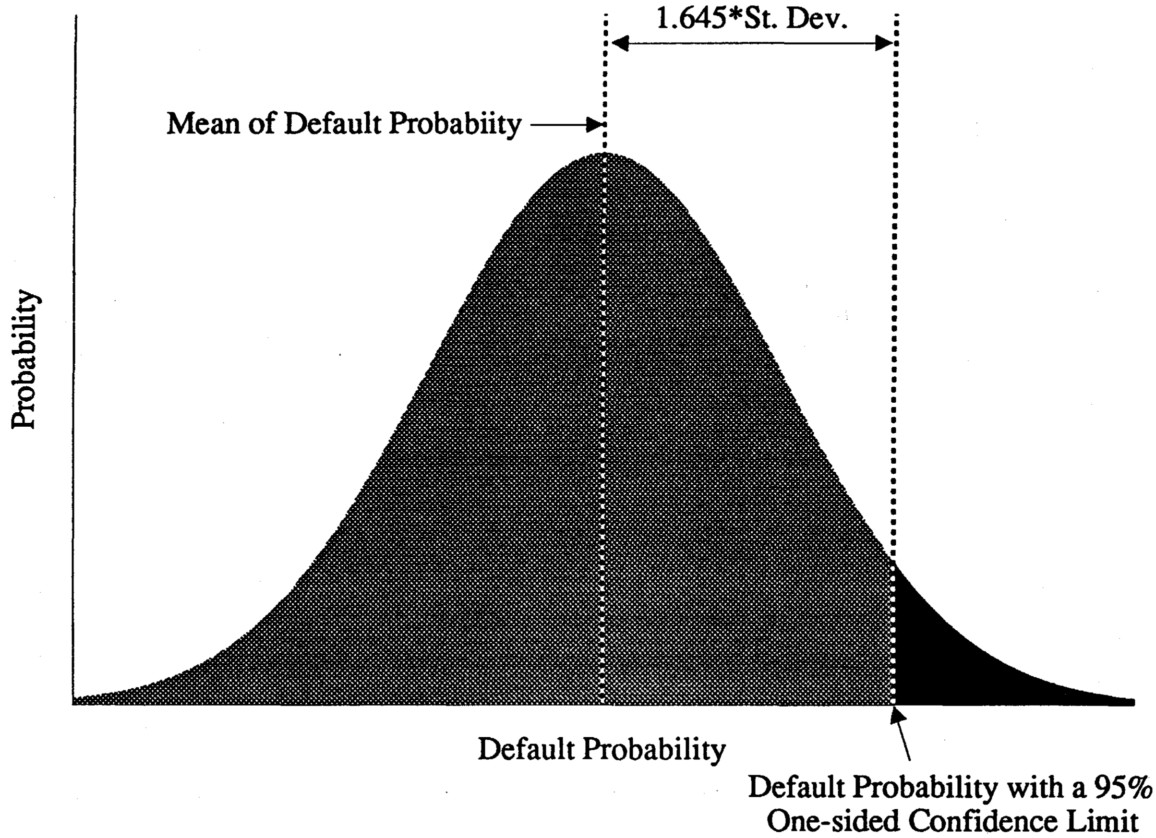
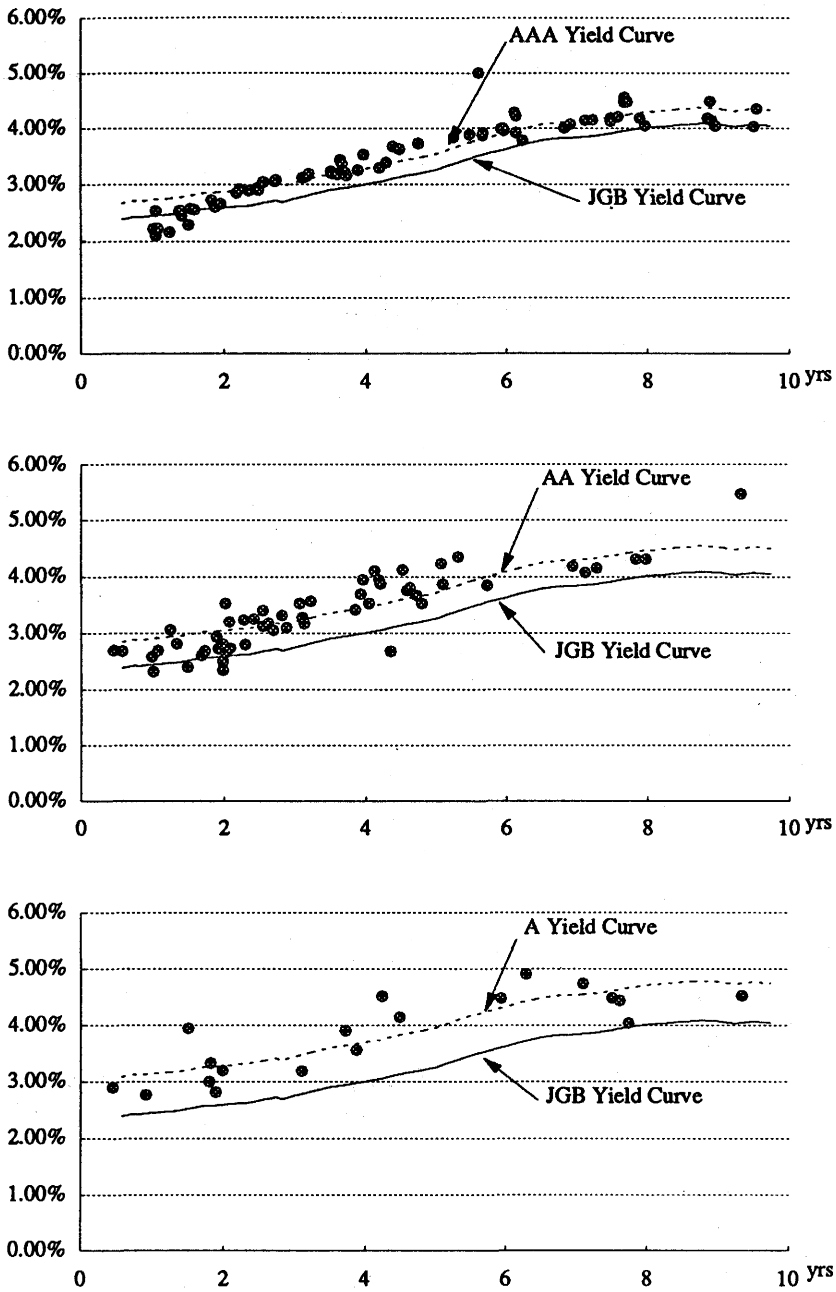


Figure 2-2 Default Probability
with a 95% One-Sided Confidence Limit



Average Yield Spread

Rating	Mean
AAA	0.28%
AA	0.46%
A	0.70%

Figure 3-1 Yield Curves and Yield Spreads of Euro Yen Bonds as of March 31, 1994

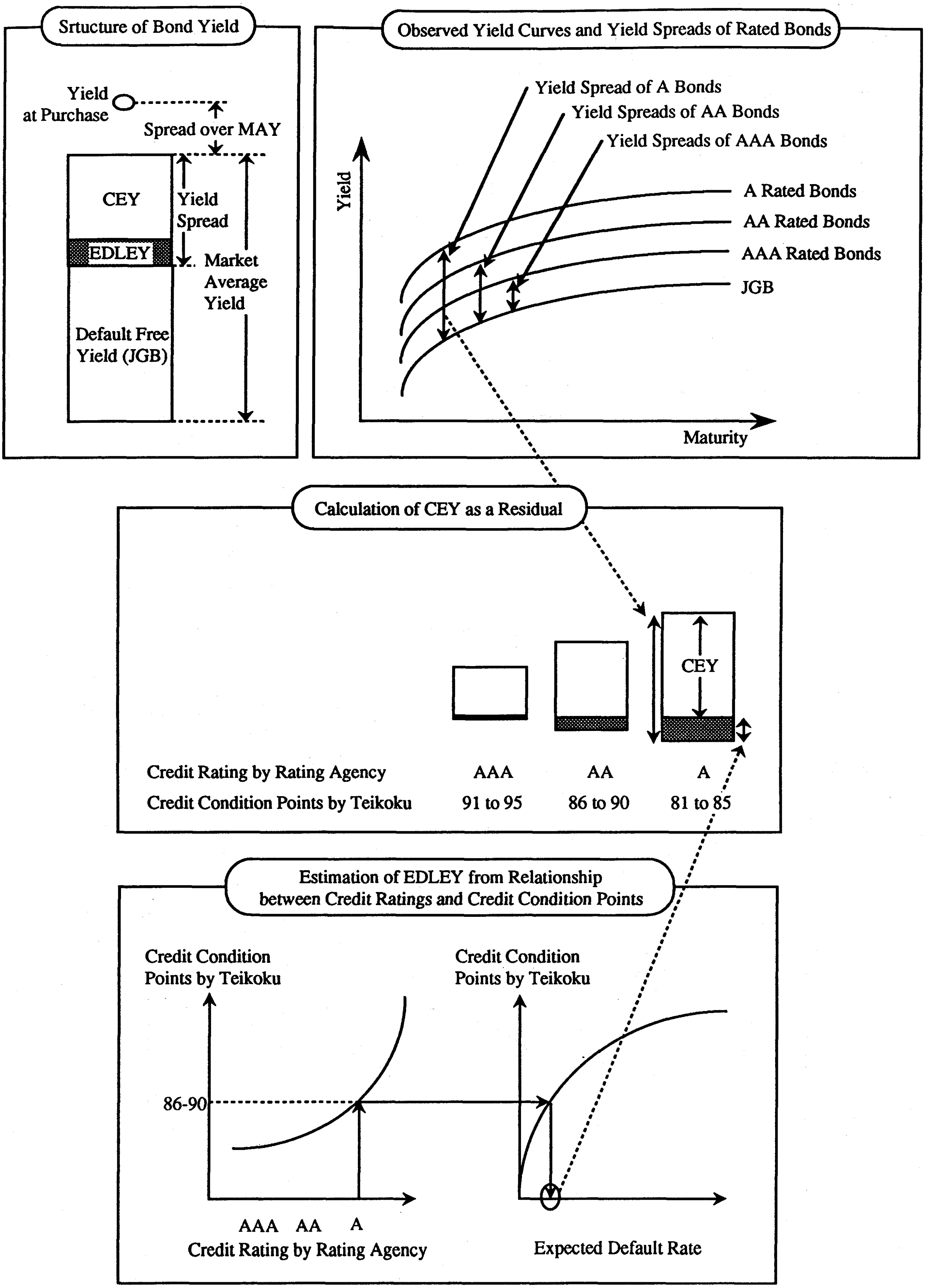


Figure 3-2 Quantification of Credit Risk of Bonds

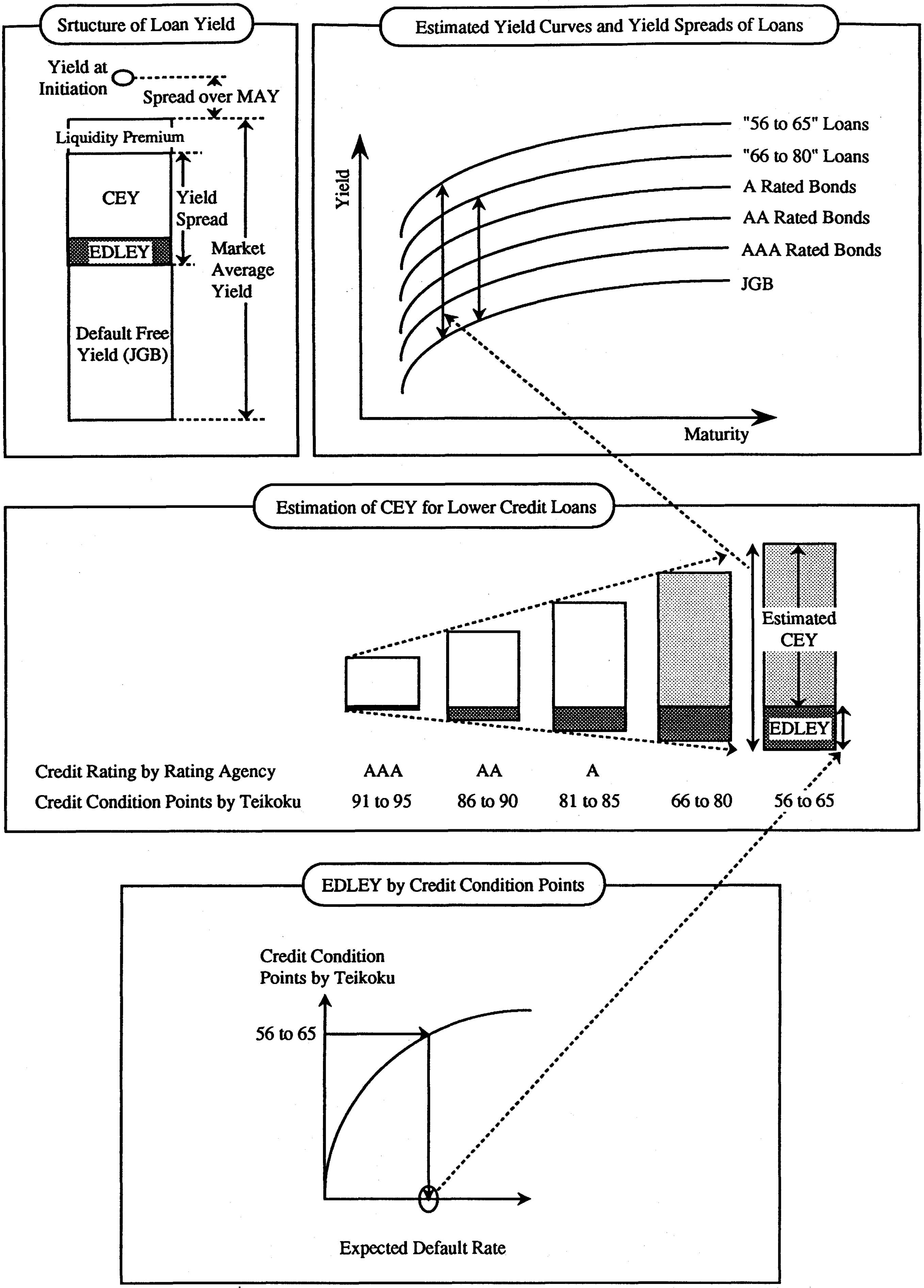
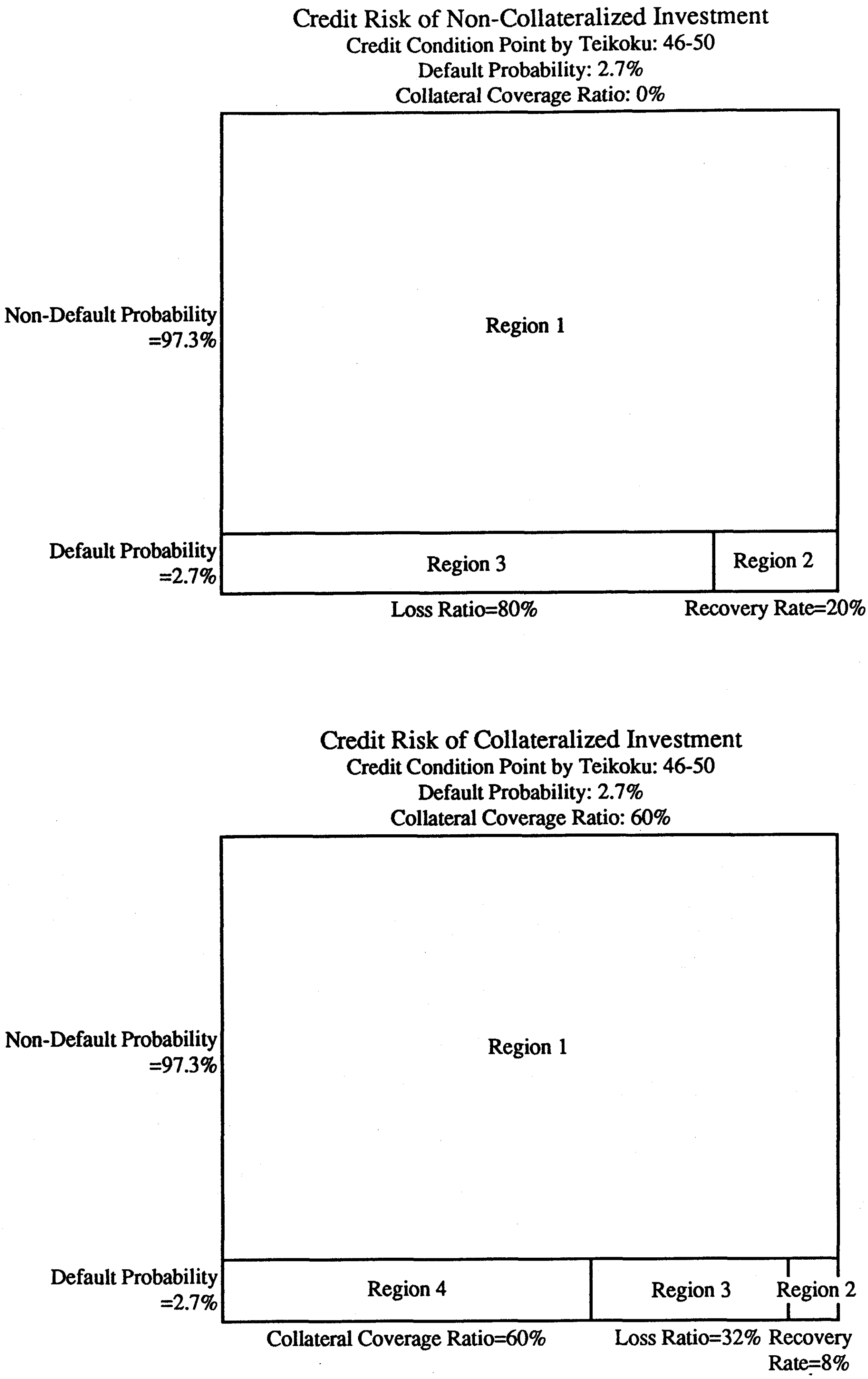


Figure 3-3 Quantification of Credit Risk of Loans



Region 1: No Default, No Economic Loss Occured
Region 2: Default, No Economic Loss Occured, Covered by Recovery Rate
Region 3: Default, Economic Loss Occured
Region 4: Default, No Economic Loss Occured, Covered by Collateral

Figure 3-4 Quantification of Collateral Effect

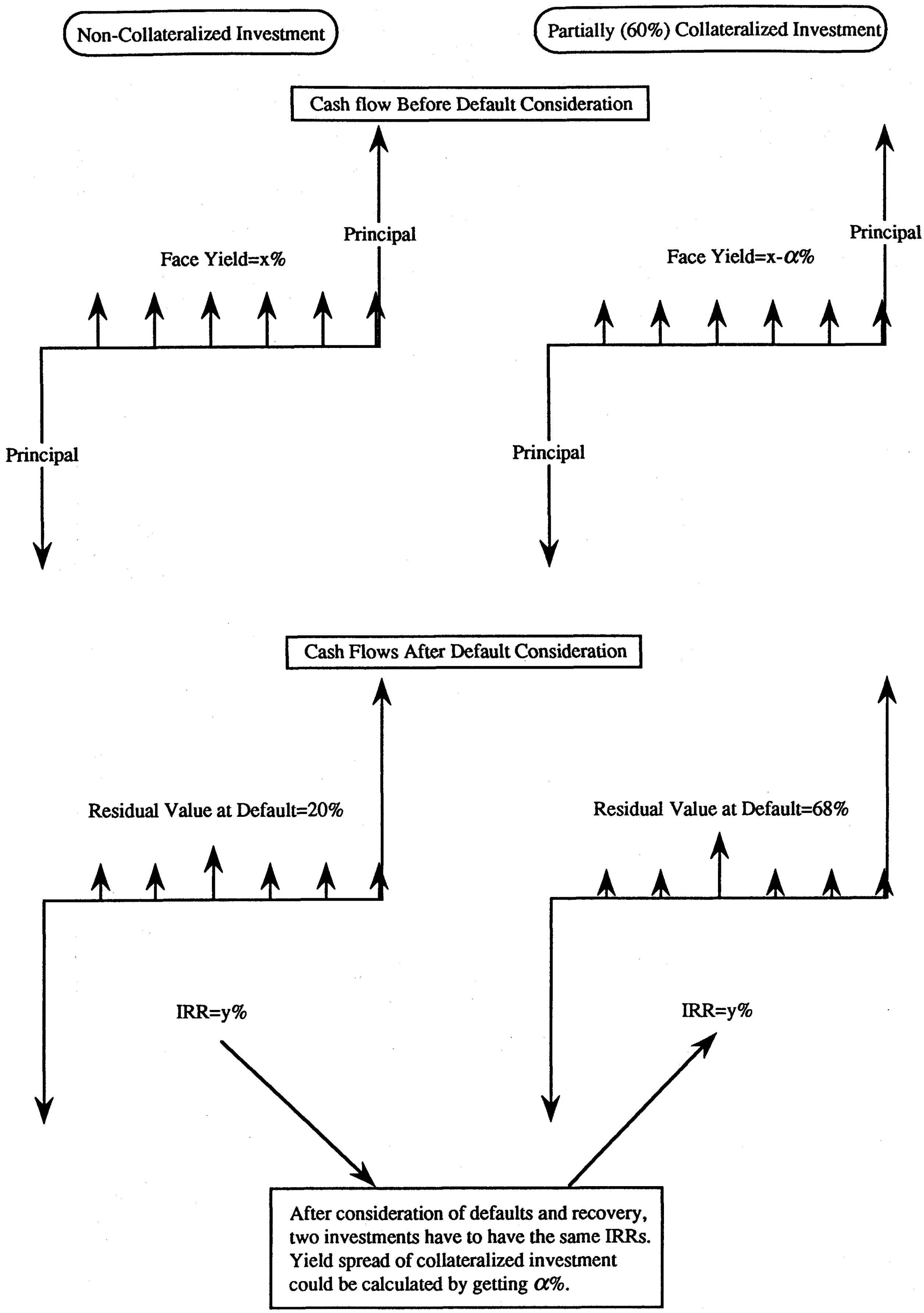
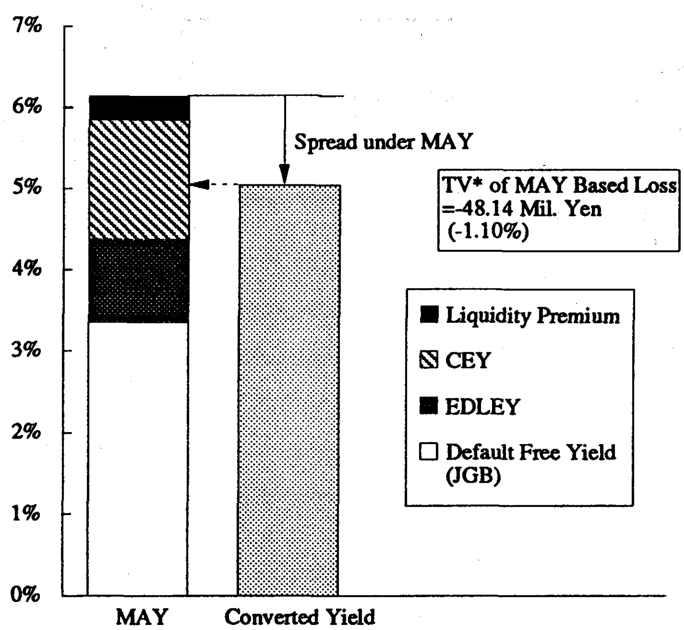


Figure 3-5 Calculation of Yield Spread for Collateralized Investment

Case 1:

Name:	A
Amount:	1 Billion Yen
Lending Rate:	Floating Rate Agreement at Long Term Prime-0.2%
Maturity:	5 years
Interest Payments:	Beginning of Each 3 Months
Principal Payment:	End of Maturity
Start Date:	February 28, 1994
Credit Condition Point:	51 - 55
Collateral:	None

* TV: Theoretical Value



Case 2:

Name:	B
Amount:	100 Million Yen
Lending Rate:	Fixed at 3.8%
Maturity:	3 Years
Interest Payments:	Beginning of Each 3 Months
Principal Payment:	Sinking
Start Date:	March 9, 1994
Credit Condition Point:	91 - 95
Collateral:	None

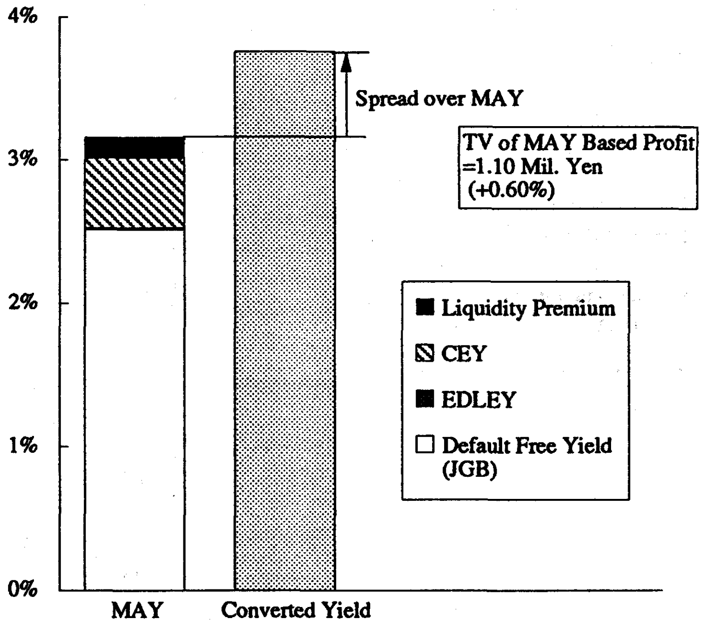
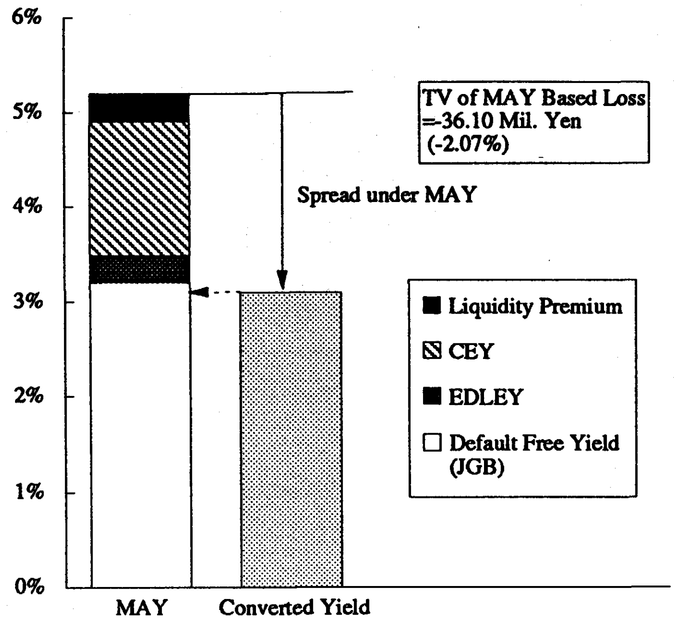


Figure 3-6-1 MAY Based Evaluation of Investments
Case Studies (1)

Case 3:

Name:	C
Amount:	400 Million Yen
Lending Rate:	Fixed at 3.8%
Maturity:	10 Years
Interest Payments:	End of Each 6 Months
Principal Payment:	Sinking
Start Date:	March 9, 1994
Credit Condition Point:	56 - 60
Collateral:	None



Case 4:

Name:	D
Amount:	200 Million Yen
Lending Rate:	Floating Rate Agreement at Long Term Prime-0.3%
Maturity:	5 Years
Interest Payments:	Beginning of Each 3 Months
Principal Payment:	End of Maturity
Start Date:	March 31, 1994
Credit Condition Point:	86 - 90
Collateral:	None

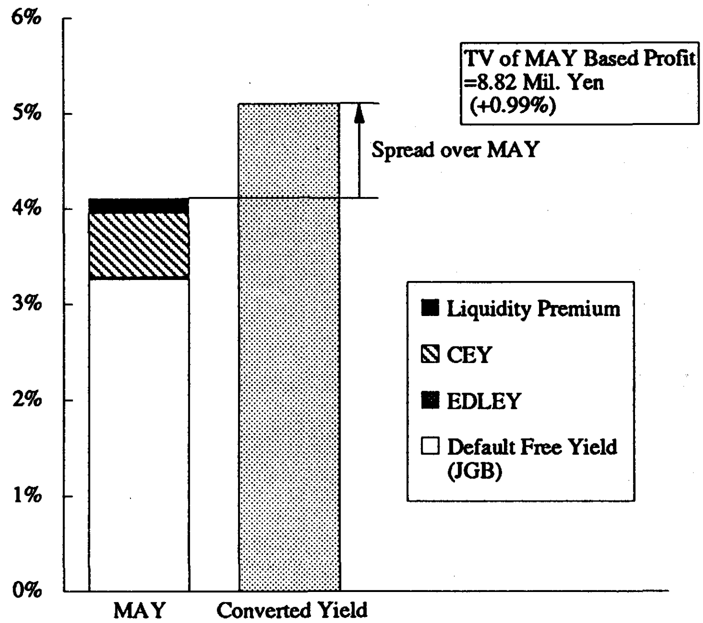
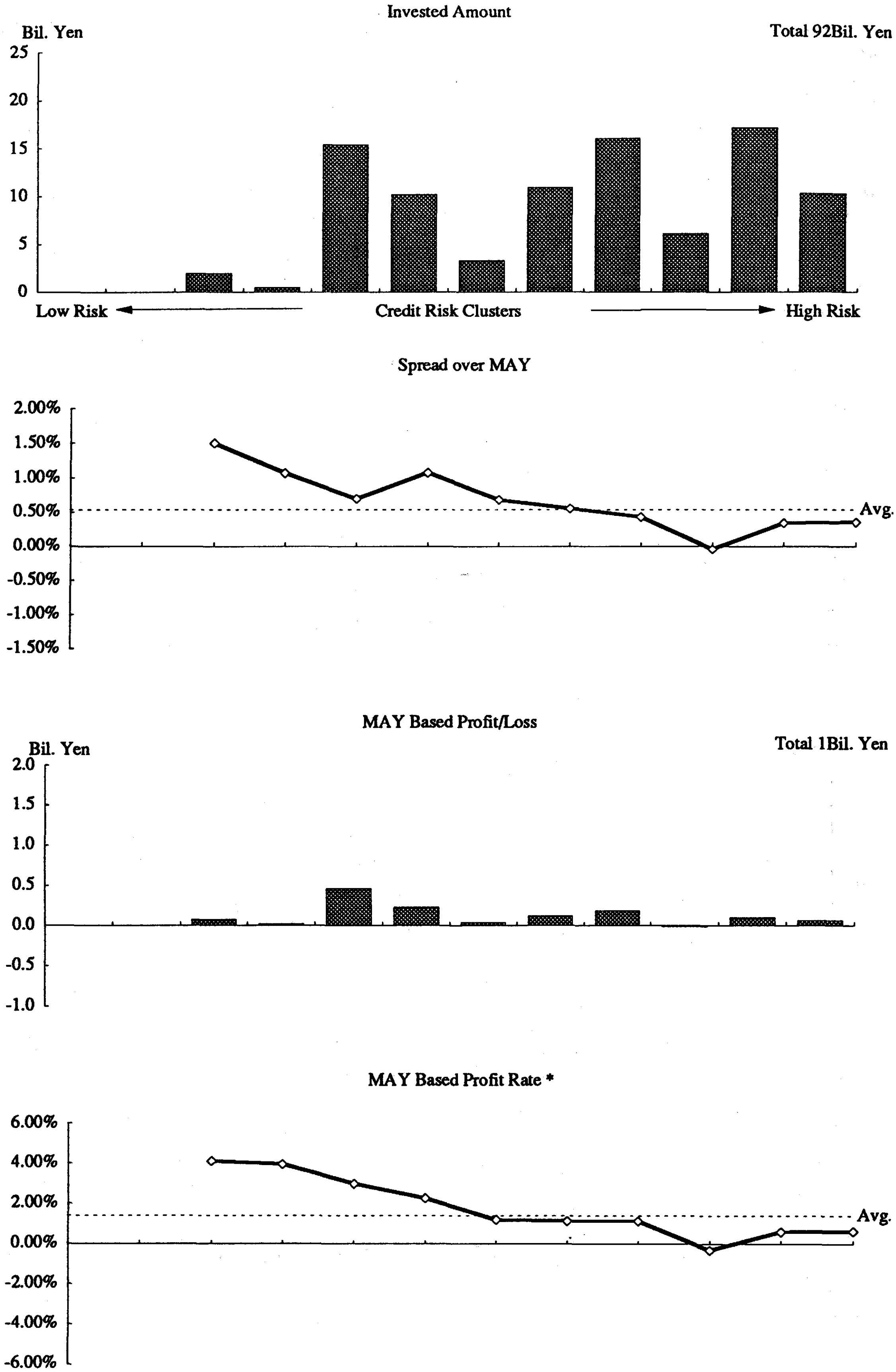


Figure 3-6-2 MAY Based Evaluation of Investments
Case Studies (2)



* MAY Based Profit Rate = May Based Profit / Invested Amount

Figure 3-7-1 Example of MAY Based Evaluation
Loans: Long Term Prime Rate Floater

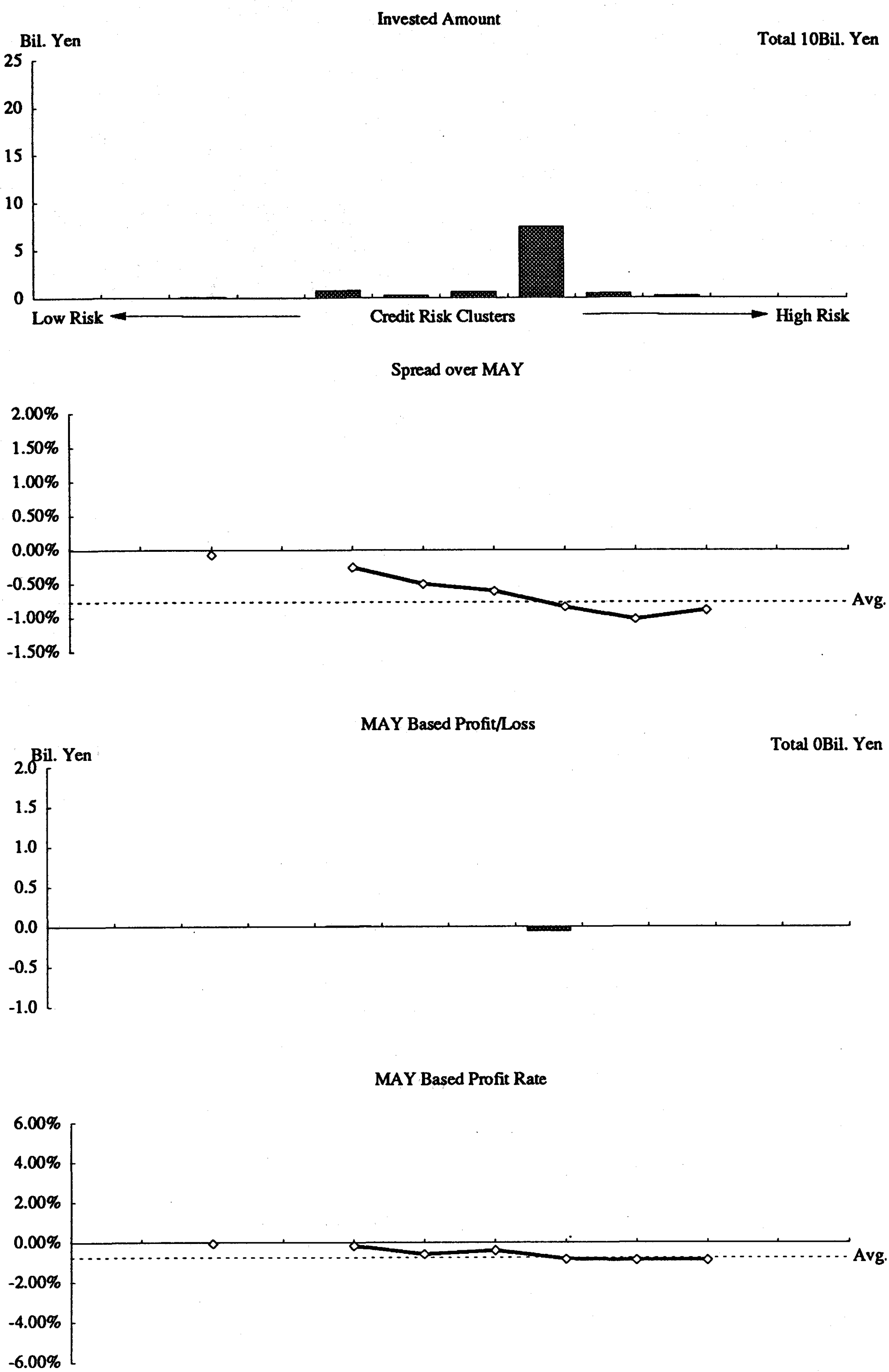


Figure 3-7-2 Example of MAY Based Evaluation
Loans: Short Term Prime Rate Floater

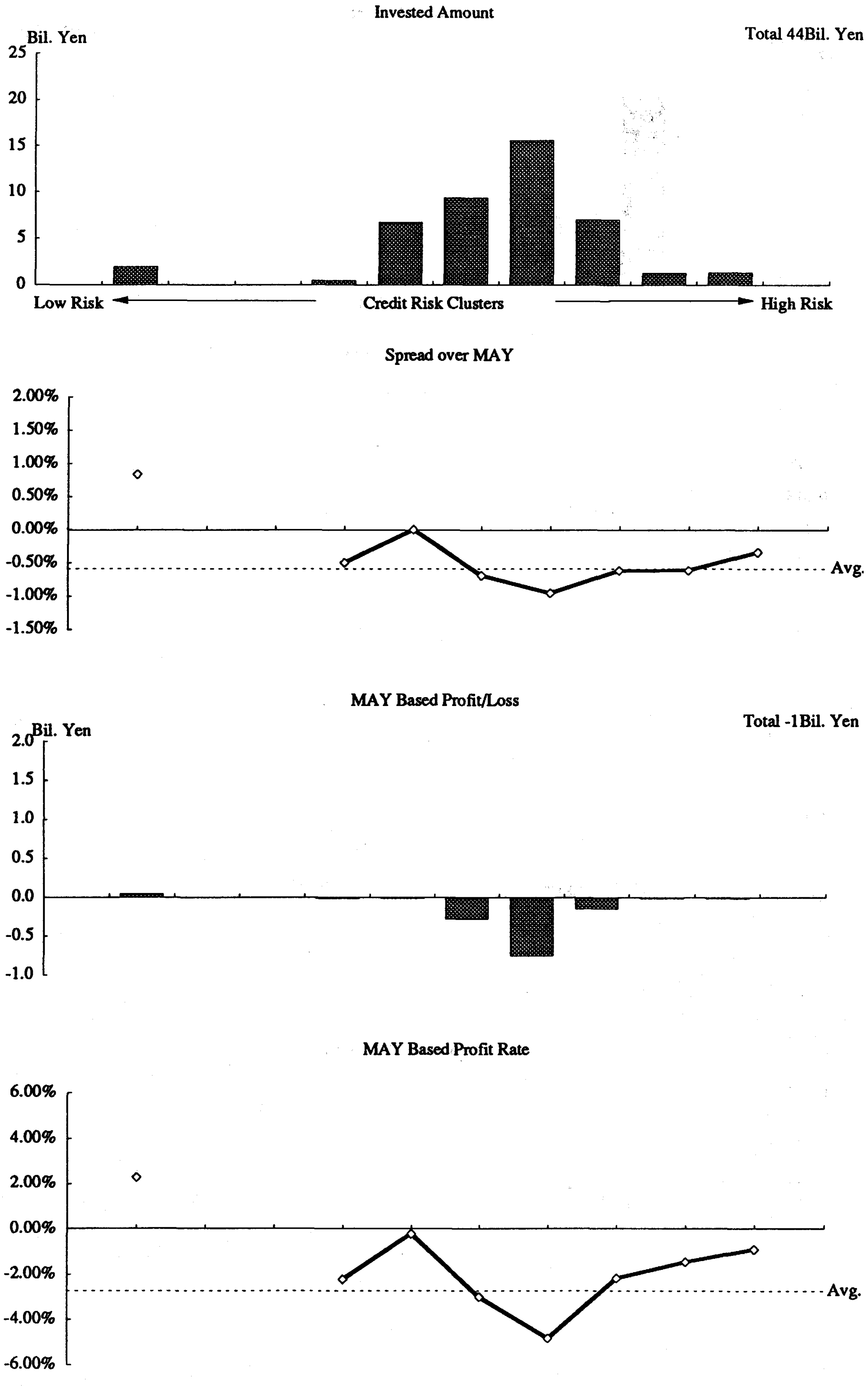


Figure 3-7-3 Example of MAY Based Evaluation
Loans: Fixed Rate

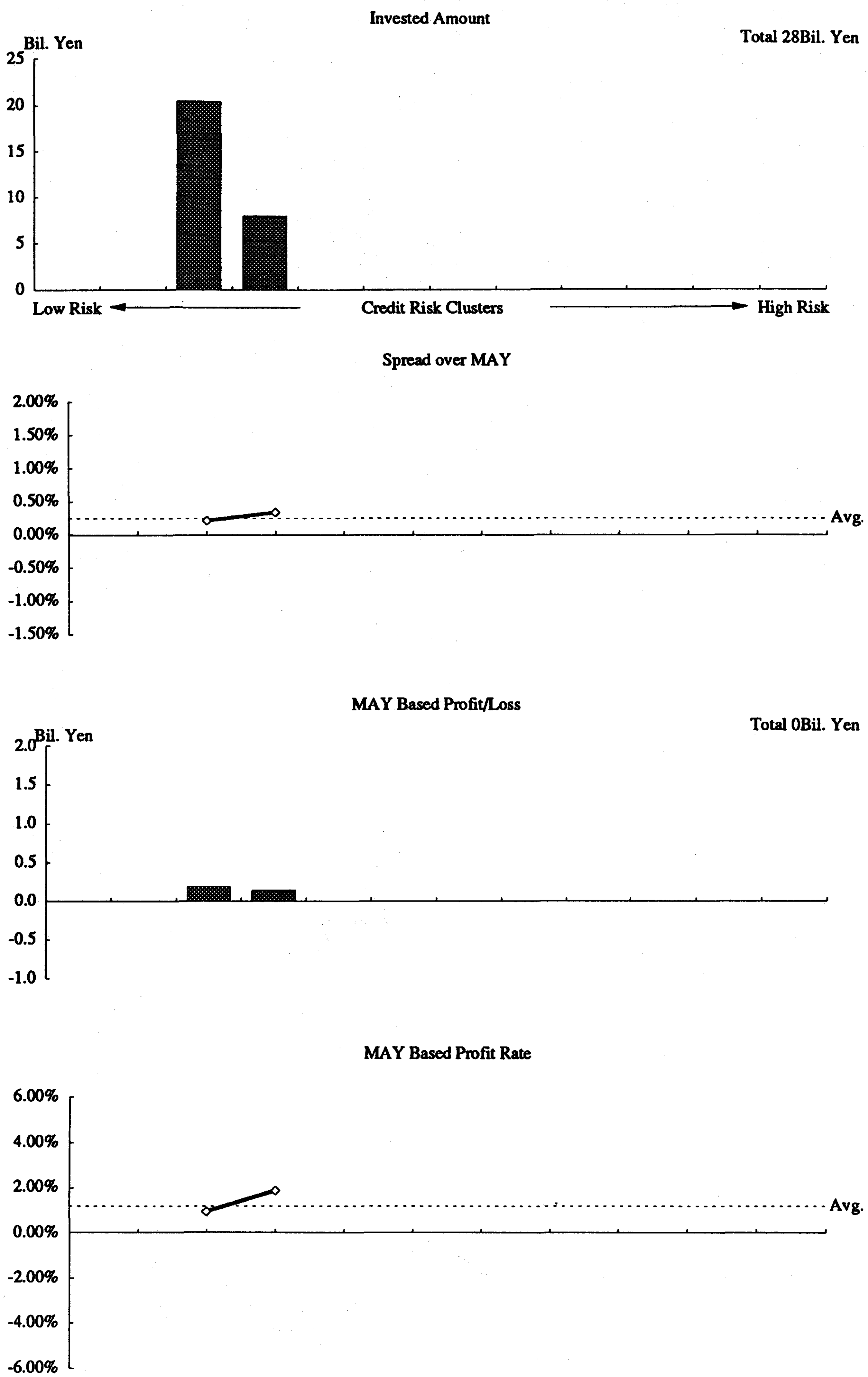


Figure 3-7-4 Example of MAY Based Evaluation
Loans: Overseas

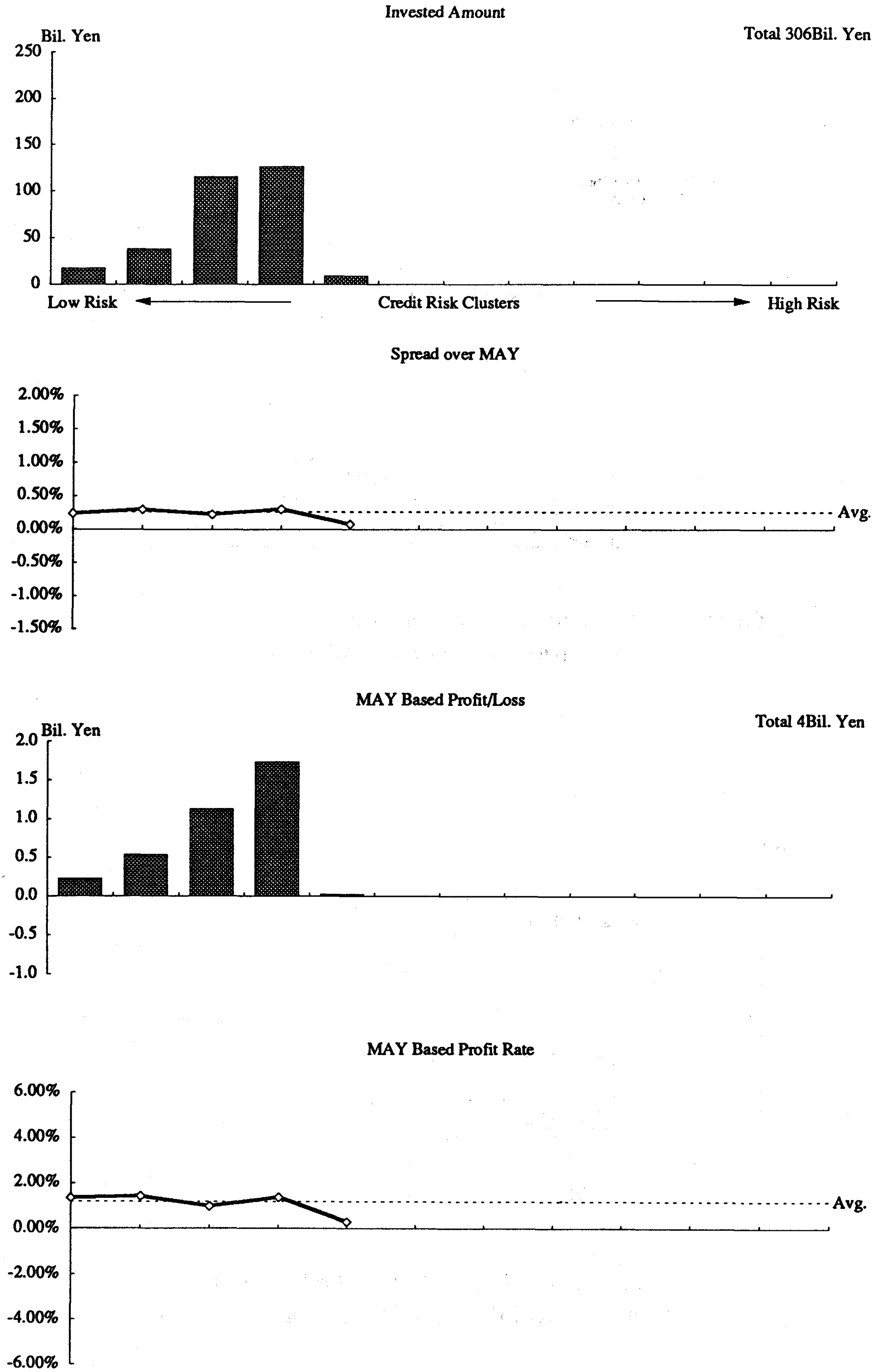


Figure 3-7-5 Example of MAY Based Evaluation
Yen Dominated Bonds

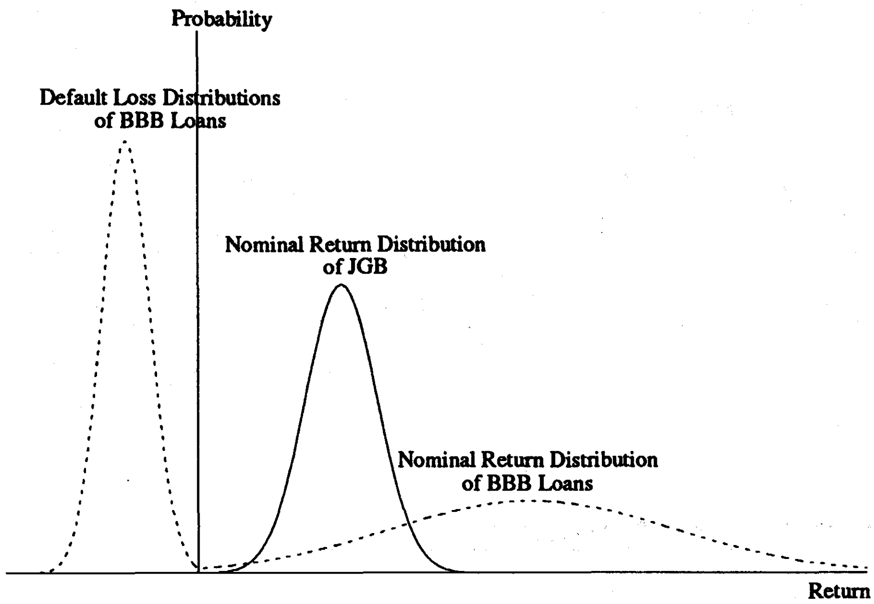


Figure 4-1 Distributions of Nominal Rerutns and Default Losses
Comparison of JGB and BBB Loans

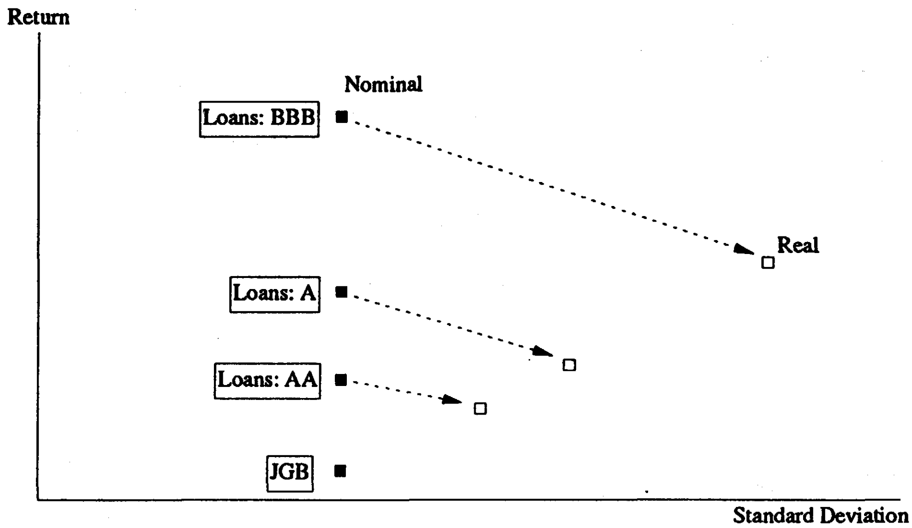
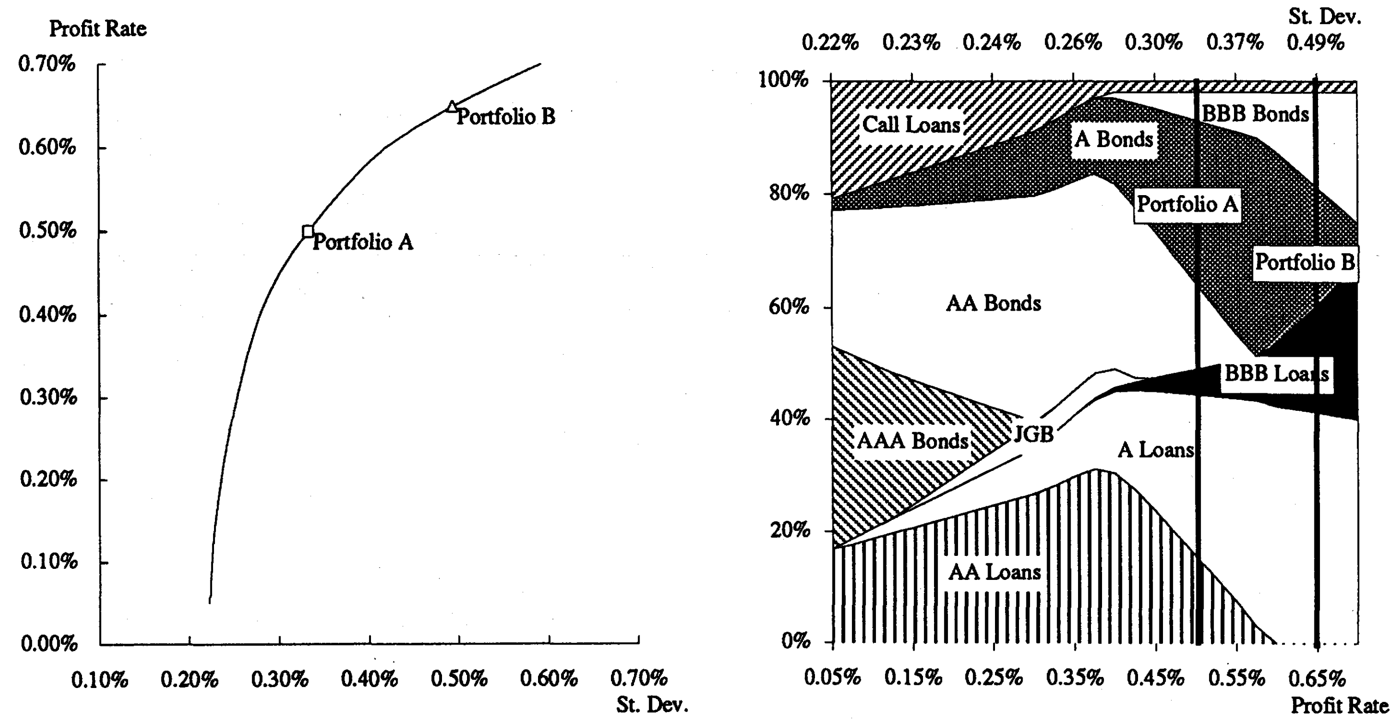
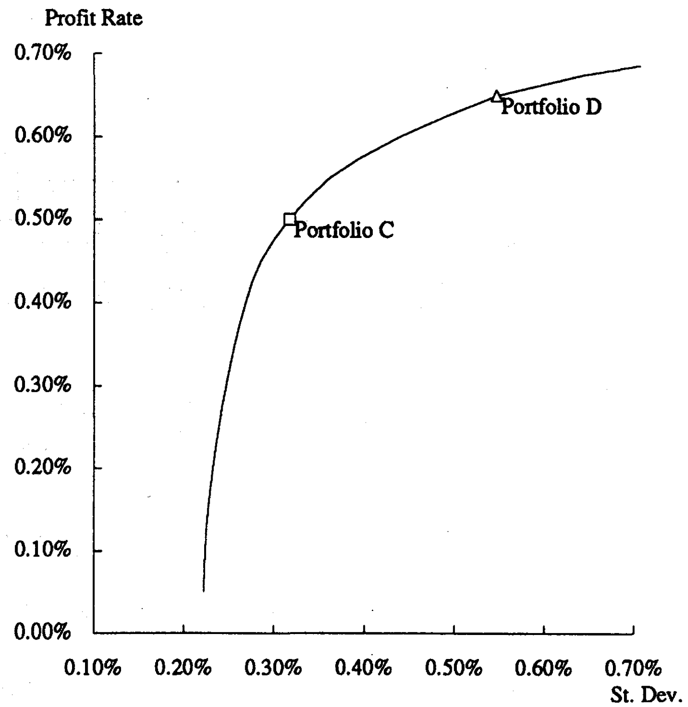


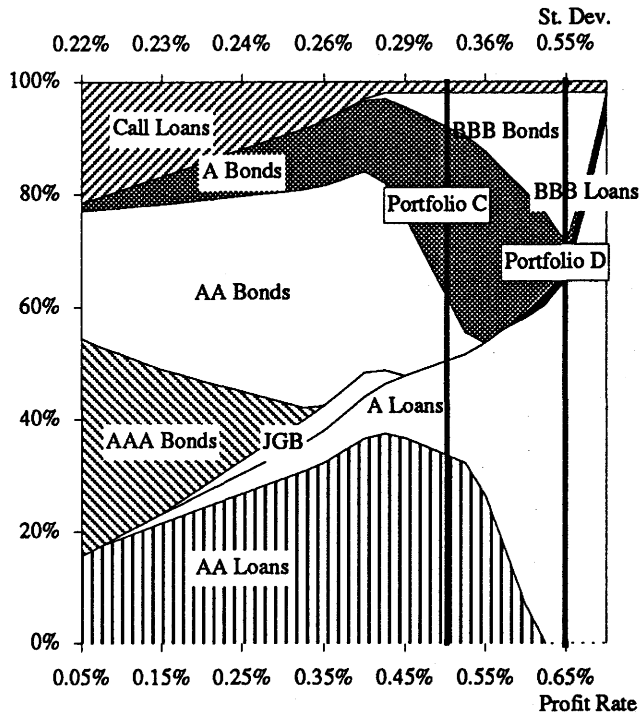
Figure 4-2 Effect of Default Probabilities
on Mean-Standard Deviation Relationship of Returns



	Profit Rate	Standard Deviation	Loans			Bonds					Call Loans
			AA	A	BBB	JGB	AAA	AA	A	BBB	
Portfolio A	0.50%	0.33%	15.5%	28.9%	4.7%	0.0%	0.0%	15.1%	28.8%	4.9%	2.0%
Portfolio B	0.65%	0.49%	0.0%	41.3%	19.4%	0.0%	0.0%	0.0%	20.6%	16.8%	2.0%

Figure 4-3 Efficient Frontier and Asset Allocation Examples
Scenario 1





	Profit Rate	Standard Deviation	Loans			Bonds					Call Loans
			AA	A	BBB	JGB	AAA	AA	A	BBB	
Portfolio C	0.50%	0.32%	33.7%	16.6%	0.0%	0.0%	0.0%	11.9%	29.9%	5.9%	2.0%
Portfolio D	0.65%	0.55%	0.0%	64.8%	1.9%	0.0%	0.0%	0.0%	4.6%	26.7%	2.0%

Figure 4-4 Efficient Frontier and Asset Allocation Examples
Scenario 2

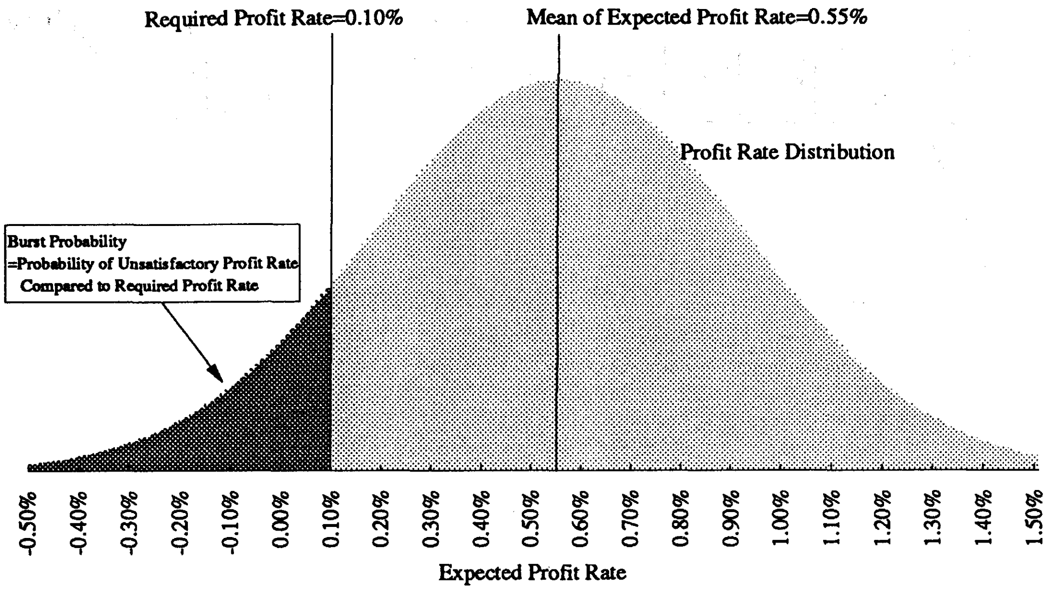


Figure 4-5-1 Definition of "Burst Probability"

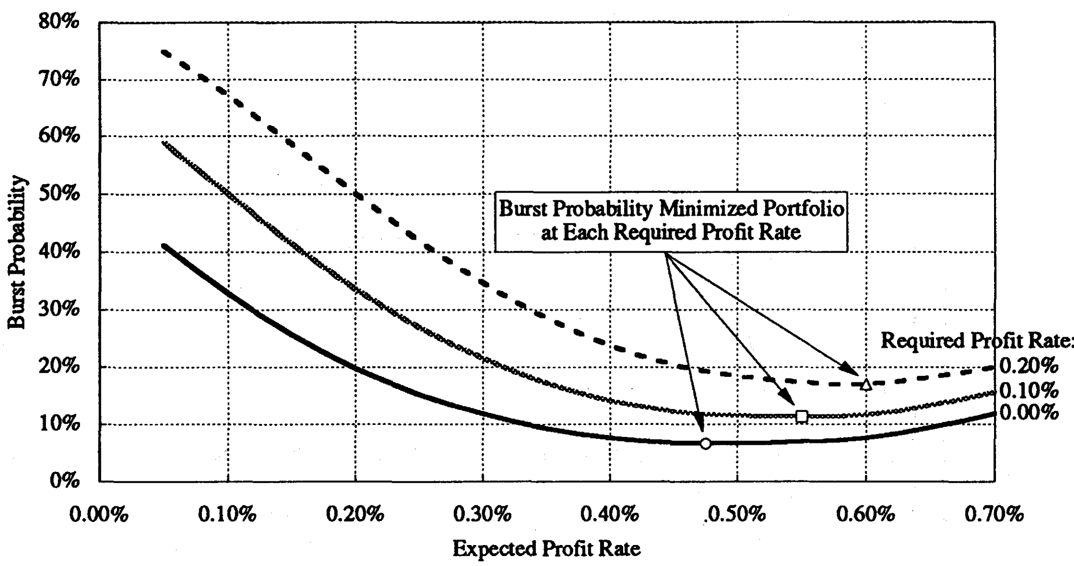


Figure 4-5-2 Minimization of Burst Probability

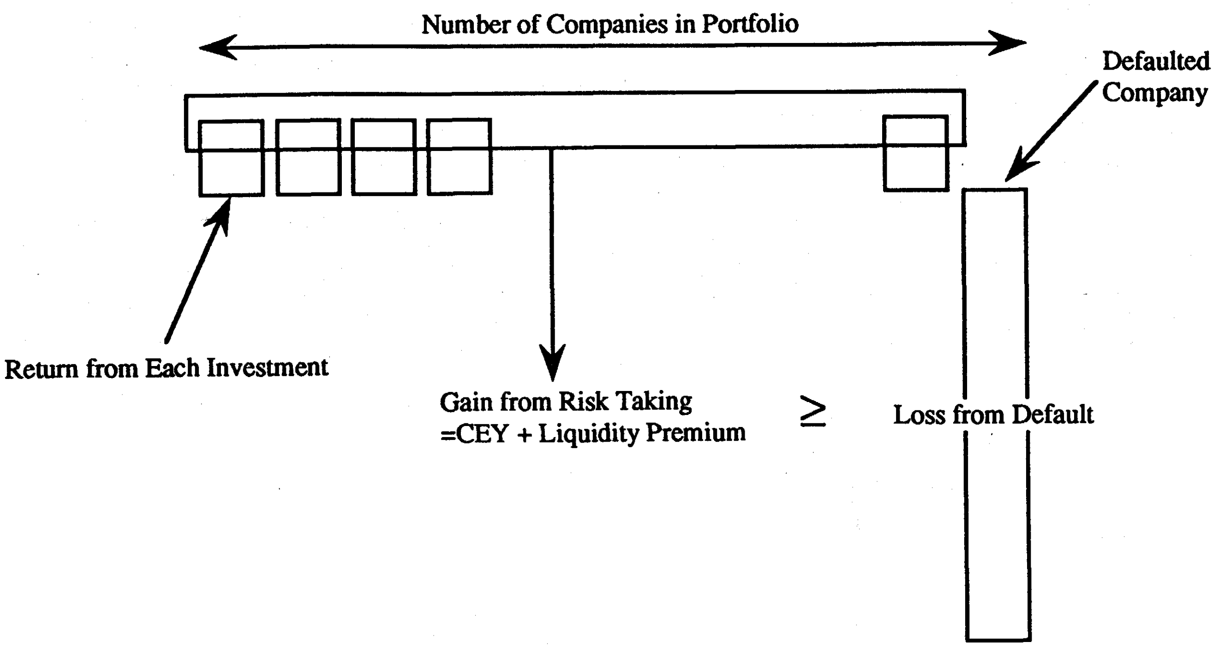


Figure 5-1 Concept of Credit-risk Exposure Control Standard

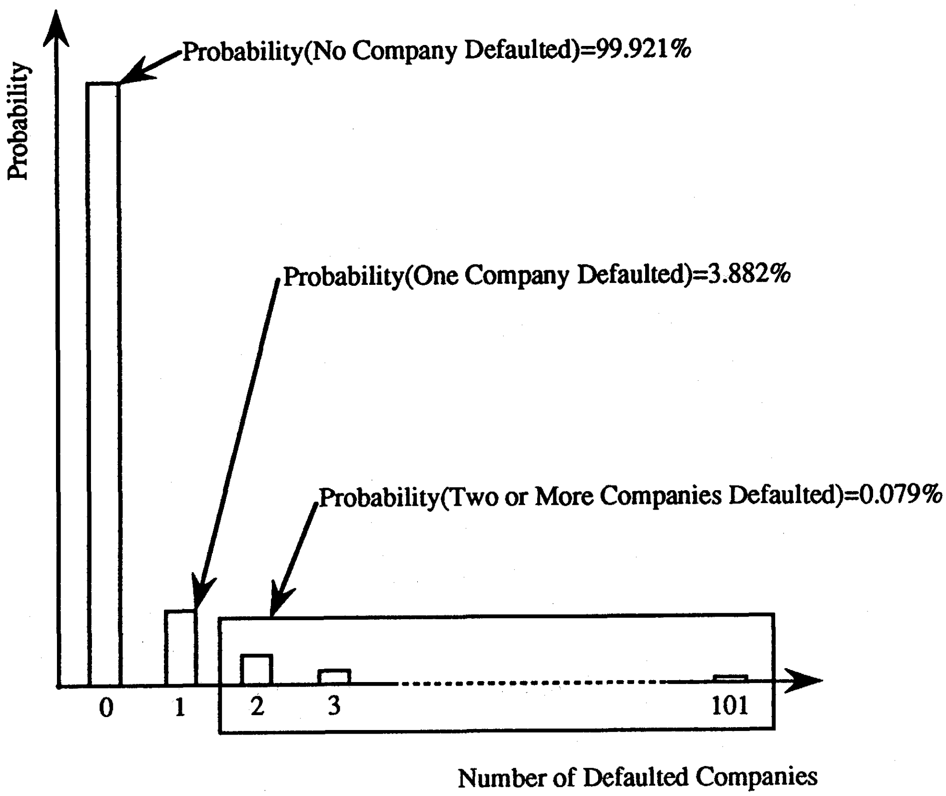


Figure 5-2 Calculation of Minimum Number of Companies in Portfolio Using Binomial Distribution