Chapter 4:

Modeling, required data, and analysis
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In the second and third chapter, my main aim was to give a clear outlook of the subject's literature and explain the customary methods of credit risk model-making in financial institutes, and the banks. In chapter two, the general contexts of the credit risk management have been described in details. I have also taken the contexts such as: economic capital, expected loss, recovering rate, loss given default, default and exposure at default, correlation, concentration, diversification, into consideration. At the end of the chapter the methods of credit risk mitigation techniques have been described clearly.

Because of the importance of the subject "model-making" in the present study, the different viewpoints and models of credit risk management have been introduced separately in chapter three, in which the customary methods of credit risk model-making in the banks, were explained clearly in details. In the present chapter, through using the introduced contexts in previous chapters, a comprehensive model which grips all different dimensions of credit risk management in the banks will be presented, and by clearing the proposed model details, this model will be tested in a commercial bank.
4.1 Overall structure of proposed credit risk modeling

The general and recognized models of credit risk management are mostly concentrated on a complex of different aspects of existing risks in the banks. Most of these models have concentrated on the subject of the customers' "Credit scoring", and different models have been presented in the same field. These models have the duty of filtering the customers, in a way that customers asking for facilities are scored according to the predicted criterions which are effective for recognizing the credit situation of customers. Here we can mention criteria Sc.

Other groups of models are engaged in "exposure limits", and its structure and framework. The aim of such models which are mostly experimental is to find the acceptable and optimum limits for credit exposures across geographical and product lines. Finally, the third groups of models intend to calculate the "capital requirements" in the banks, so that they can cover the derived risks from the banks procedures. In any case what is important here is that the mentioned models and patterns are minor ones, and each of them manages a part of credit risk aspects. The aim of the present study is to give a comprehensive and applicable model for managing all the credit risk management's aspects and dimensions in the banks. The following diagram shows the general framework of the proposed model.
As it is shown in the above figure, customers' credit scoring is the most important part of credit risk management in the banks. As the first of credit risk management, the banks have to have a developed system of recognizing and assigning rates and scores for their customers' credit. Getting to know the credit standing of the customers, will give the banks a chance to determine the amount and level of their transactions according to their customer’s situation. Thus, the banks, by having true recognition of their customer’s credit situation, and also regulating the level of transactions and the amount of the facilities given plus deciding about the amount and the kind of collateral received from their customers on the basis of the risk sustained on the banks, can prevent the unexpected risks. This subject is a part of the proposed model.

The second part of the proposed model is related to determine the optimum level of the exposure limits of credit pillars in the banks.

As it is quite obvious, the risk and loss implemented on the banks are the result of the quality and quantity of the facilities granted to the customers. If the banks do not benefit from a system for determining the optimum limit of authorization in granting facilities, then some of the credit pillar may sustain irreparable damages to the banks. For this purpose, the banks should have a system that through determining the amount of authorization of the banks credit pillars in granting facilities, can prevent irreparable damages to the banks, and therefore another part of credit risk management will be effective in the banks. In any case, this fact has been accepted that designing the tools and methods of credit risk management in the banks will help the banks to reduce the risks sustained, but we should notice that these risks will never be omitted completely. This means that even by having developed an innovative model of customers’ credit rating, or determining the limits of credit authorization, there will still be an amount of risk sustained on the banks. The important point in here is that the banks have to have
system for determining the necessary reserves for covering and compensating these risks. In the proposed model, this subject has been taken into consideration, and determining the economic capital for the banks has been propounded as the third part of the proposed model of a comprehensive risk management.

The three mentioned parts are considered as the main parts of the proposed model. The important fact here is that the mentioned part should be related together from the input and output variables point of view. In this model, you can clearly observe this connection, in such a way that some of the output variables of the exposure limits of credit pillars are actually the output variables of customers’ credit rating. The following figure shows the parts, process, and the connection of variables in the proposed model.

As it can be observed in the above figure, the proposed model of credit risk management has three completely separated parts. However, these parts from the view point of input and output variables have an internal connection. Although these three parts will be explained comprehensively in the next parts, but for the purpose of creating a clear outlook of the model and the study done, a
summary of the designing process and estimating the proposed model in accordance to the flowchart will be given.

In order to design and estimate the model's coefficient, necessary data from some of credit files have been collected. Collecting data from these files can differ depending on the model chosen. By considering the known criterions for measuring the customer's credit, we have used 5C criteria, in order to collect data from the credit files. Then the mentioned data have been entered into the logit model and the related coefficients are estimated. Through using such model, the bank can estimate the credit score of each of its customers, and then put these scores in different categories, and as a result rate the bank's credit customers. This process has been introduced as step one in the above figure. In step two, in order to achieve the probability of default of all the loans given to the bank's credit customers, the data related will be entered into the designed model, and the output will be the calculations related to the probability of default of customers.

In the second part which is related to the designing and related estimating of the exposure limits of credit pillars, the input variables which consist of initial data matrix, resources' growth rate, and categorized customer's PD's is processed according to the designed model. The result of the model's process is in fact the estimation and determination of the optimum exposure limits of credit pillars. The details of the design have appeared in the coming parts.

In the third part, the capital requirements for covering the risks derived from the bank's activities are estimated. As it has been mentioned previously, the amount of the loans given by each of the credit pillars has been considered as value at risk. On the other hand, by using credit scoring model we can estimate the average default rate, or in other words \( \mu = \sum \rho i \) for each of the credit pillars. By having these two groups of variable, and through using Credit Risk Model.
model, we can estimate and evaluate the capital requirements for the banks.

4.2 Credit Scoring

As it is known, the major part of banking system’s functions is summarized into two different groups. One is collecting deposits which is usually in the forms of Gharz-al-hassaneh (usury free accounts), short term and long term deposits, and the second one is the process of allocating sources which contains granting all sorts of loan and facilities in the forms of joaleh, installment payment, Gharz-al-hassaneh, Mosharakah, and Mudarabah. The banks should also pay more attention to absorbing deposits and prevent its cash flow towards other financial markets, while the major profits of the banks is provided from such channels, and not paying proper attention to such matters would cause lack of cash flow, and puts an stop to allocating facilities in other places which can help the economic growth of my country, IRAN. Therefore; in order to solve such problems, first we should recognize our customers in a proper way and then their credit worthiness should be evaluated. In the past, the customers were recognized through their credit worthiness, while in such case personal preferences were involved and in such method a unique and single criterion was not used. Today there are methods, that by using definite criterion, a person can be evaluated without personal interferences. These methods are divided into two parts: “Artificial Intelligences Method”, and “Statistical Method”, from which artificial intelligence method is of the most flexible one among the credit assigning and credit worthiness methods between the customers. As it has been studied, these methods because of their learning nature can adapt themselves to any kind of information entering these models, and they even have the capability of updating themselves with new data.
Other than these advantages, there are some twists and turns, which have made the application of such methods very difficult.

The second group is "statistical methods" which are a wide range of parametric models such as "linear probability model", "logit and probit models", and "discriminant analysis", and also non parametric ones such as "decision trees model", "mathematical programming", and "nearest neighbor model". Here, we are going to study one of the parametric models under the name of logit models.

Based on the studies done previously, it shows that in comparison with other models, this model has more efficiency. By considering the kind of facilities granted by banking system, this system has got two different categories of customers, "real and legal customers". For each group a special variable exists. In this Thesis the legal customers are being studied.

The overall modeling of credit scoring has been illustrated on figure (4-1). Here, the detail of this process is being shown in the following Figure:

Figure (4.2): Credit scoring process
4.2.1 The background of credit scoring:

The background of evaluating credit risks goes back to 1936 and Fisher’s article. In this article “Fisher” has used the 5 criteria distinguished by experiment and not by statistical methods. After Fisher, in 1941, “Durand” tried to know the important parameters according to the loan givers and the specialties which were important from the statistical point of view. Durand is considered as the founder of credit scoring systems in the present time. Toward the end of 50’s, credit cards were welcomed by the public. This caused a huge size of demand; therefore; the needed time for decision making became longer and the need for credit scoring grew as well. By the end of 50’s a larger number of companies wished to improve and develop their credit scoring system, among which we should mention the most famous one under the name of “Fair Isaac company”.

“Bogess”, is the first one to mention the usage of computer in studying a large set of data, in his article. He tried to use complicated statistical tools in the way of improving the exact models of credit scoring.

There are some studies done in the area of risk management in our country, which we can mention the articles of “Reza Shiva PH.D.”, and “Hassan Mikaeelpoor PH.D.”. In their articles, they have explained different kinds of risks related to risk management in the area of banking, and have also mentioned a number of calculating methods such as “value at risk”, and “testing method” in critical conditions.

4.2.2 Usage and importance of Credit Scoring:

Credit scoring as a means of risk management, is a system that is used by creditors in order to evaluate the competency of loan or credit card applicants. This system considers the past credit of the applicant such as his income, job, house ownership, the length of employment, and delayed debts, to understand that how and when
and during what length of time the applicant has paid his bills. In other words, credit scoring is a statistical method based upon the person’s past which is used to predict the probability of refusing the applicant’s loan, and also to determine the necessary condition for the applicant to receive a loan. These models are used as a quantitative method to put a value on the credit customers.

When the number of credit customers increases, or in other words the volume of creditors job goes far beyond expectation the need to use systematic and efficient methods to evaluate the risk of credit scoring increases.

Although it is still possible that the small creditors, use unofficial credit metrics, today a large number of companies use official credit scoring methods. There we should mention that, although no system is exactly complete, credit scoring can at least act correctly according to unofficial methods. We should also consider that in most cases, credit scoring gives correct results and prediction which can be the real reason for using such method. Generally we could summarize the use of credit scoring as follow:

- Predicting the probability of loans’ non-payment.
- Distinguishing reliable customers from non-reliable ones.
- Decreasing the time of credit decision-making.
- Decreasing the costs of inspecting the credit requests of small enterprises.
- Improving and updating Data System.

4.2.3 The advantages of credit scoring methods:

As it has been told, the new methods of credit scoring have some advantages in comparison with the old ones. The advantages are as follow:
• **Models are more real and reliable:**

The segregating models usually depend on non-systematic criterion, while credit scoring methods are based on statistical analysis and data, therefore; while these models use definite and equal criterion for all loan receivers, they are more real and reliable.

• **Credit scoring as a modern replacement for traditional and old methods:**

Since in the past traditional methods of decision making were mostly used, then we study the differences between traditional and latest methods.

• **Traditional methods of credit granting:**

In the past, the bankers reviewed the customers’ requests for loans according to the old and traditional methods, and then approved it on the basis of qualitative judgment. In this situation, the banker preformed the most important part of traditional loan granting process.

• **Modern methods of credit scoring:**

In comparison to traditional methods, the modern ones act as follow:

First the applicant sends his loan request through telephone or e-mail and then on the basis of the customer’s credit history and information send, his request is reviewed by computer, and in the end his request is either accepted, or denied. By using the modern methods of credit scoring, the application form of the applicants can be accepted by the bank in a few hours and with the least cost.

• **Rapidity in loan granting procedure:**

The credit scoring system is likely to shorten the needed time in credit approval process. In a study done by “Business Banking Board”. It is shown that in the past the loan facilitator used to spend
two weeks on this process, while now the average time for granting loans in traditional way is only 12 hours, whereas using other system of credit scoring can lessen this period of time to one hour. Of other advantage of credit scoring we can mention; improving services for the customers, qualitative decisions instead of quantitative ones, better decision making, and less expensive process.

4.2.4 The limitations of credit scoring:

The correctness and accuracy is one of the most important factors in credit scoring systems, while if there’s no accuracy, then the advantages of such model can be questionable. The accuracy of a credit scoring system is directly related to the development of such model.

- The data on which the system is based on and formed should be a combination of overdue loans and liquidated ones.
- In addition, the data related to the model should be updated and it should be estimated again.
- A good model is a model that in recession and prosperity conditions has the power of predictability. Therefore, we have to use the data related to the time of recession and prosperity. It means that the considered time used in these models should embrace these periods of times as well.
- From the view point of using credit scoring, the smaller banks have limitations, while the management of their limited loans will not be cost effective, but loan facilitators in larger scales can use such models.

4.2.5 Different models of credit scoring:

Among parametric credit scoring models, we mention linear probability model (LPM), discriminant analysis, artificial neural network (ANN), Genetic algorithm, “logit and probit models”. Among non-parametric credit scoring models we can mention mathematical
programming, decision trees model, analysis hierarchy process, nearest neighbor model and expert systems.

I. Discriminant Analysis:

The first classic method which was used for credit scoring was on the basis of discriminant analysis. For the first time in 1967 "Altman" used discriminant analysis for predicting companies bankruptcy, and in 1977 on the basis of categorizing and new definition of bankruptcy at that time, he made a revision on the mentioned model. In 1955, he adapted his model to the new markets, and recently in the year 2000, the aforesaid model was updated according to new information. The usage of such model is categorizing people and institutions into two or more groups.

The application of this model for the banks is as follow: the customers are divided into two groups. G1 are those customers whose application have been accepted and G2 are those with refused applications. What we have to do is categorizing the new applicant through using parametric vectors $X$ (Show the characteristics of the applicants) $= (x_1, x_2, \ldots, x_k)$. Analyzing the differences, we can solve this problem by making diversity function $\lambda'X$, which here $\lambda$ is indices vectors, and the allocated weights is in Xi standards. This model, by forming the largest possible difference, will estimate these quantities. This method in order to estimate the credit risk of institutes (legal entities), only makes use of financial variables, such as profitability, ratio of debts to the net assets (leverage), the size of the institute, and etc. for determining credit risks in people it uses variables such as income, age, and job. In other words, this technique forms a linear combination of descriptive variables, in order to achieve different function from which the rates achieved are in fact the scores.

$$Z = \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 \quad (1)$$
Categorizing by using aforementioned models will be very easy. We should compare the scores achieved to the threshold limit, that if the score of the applicant is higher than the limit determined, he belongs to G1 and if otherwise, it will be in G2. After gathering the scores we should take them to histogram curve, whereas the curves of both groups are over one another, then our model does not have a proper function, and if the differences between groups are a lot, then our model will have a better distinctive function.

II. Neural Network:

Studying neural network started from 1943. If a mathematic model is to act as a natural neuron, then it should take the very shape of it, and receives its characteristics. “Dandrits” and “Axons” are the most important parts of “Neurons”, while they receive the signals, and give the processed data to other neurons. Another important part is “Sinups” which usually process the data. They relate the axons to the other neurons dendrite. The function of mathematic neuron model is relatively simple. By using a definite function, it process the information received from dandrits, and if the nearing signal exceeds the “stimulant threshold”, then they forward the information through Axons. The most prominent characteristic of such neurons is that according to the data received, it changes its function repeatedly, that it means “learning”. The “Sinups” play an important role in learning process, in such a way that they are capable of strengthening or controlling the received signals from other neurons.

In neural model, the change and balance of these weights is called “learning”.

Since the time that artificial intelligence systems such as artificial neural network and genetic algorithm, have been designed and introduced, using them in financial investigations and credit categorizing became most popular and is still increasing. The usage of different
artificial neural network and genetic algorithm, or the combination of them with other rules such as “Fuzzy Logic” and “Bayesian statistics” has made a potential model for credit categorization. In some studies in which the relative exactitude of these systems has been compared to other statistical models, the results have usually shown a higher exactitude in artificial intelligence systems.

Therefore we can draw a diagram as follow for these systems:

Figure (4.3): A simple model of neural network

Neural network in its simplest form are similar to linear regression which is as follow:

\[ y = w_0 + \sum_{i=1}^{n} w_i x_i \]  \hspace{1cm} (2)

Its activating function then can be non-linear function such as logistic function and as follow:

\[ F(u) = \frac{1}{1 + \exp(u)} \] \hspace{1cm} (3)

in which \( u_i \) is:

\[ u = \alpha + w_1 x_1 + w_2 x_2 + \ldots + w_n x_n \]
The differences between statistical techniques and neural network:

- The relationship between inputs and outputs of each group is not necessarily linear.
- Neural network can minimize the gap between the real extent, and the predicted amount.

Neural network takes advantage of learning process which itself uses feedback circle. These networks by observing the difference between the models output and the real extent, will understand that the weights of the models should be changed. The law which causes the balance and the change of weights is called “Delta Rule.” The size of the changes which should happen in the weights is related to a parameter under the name of “learning Rate”. The reason for using neural network in its full capacity is the relating capability of such network. For example, many of the financial ratios can have a linear link such as profitability criterion which is related to each other through general factors as net income resulting from profits gained, or income previous to profit and tax. This multi co-linearity is one of the weaknesses of linear models, while the other system is completely free of such.

III. Linear Probability Model (LPM):

Linear probability model is a regression model in which the amount of dependant variable selects the numbers 0, and 1. This model is as follow:

\[ y = b_1x_1 + b_2x_2 + \cdots + b_kx_k + u \]  

(4)

y : dependant variable (result of decision making)
x1 : Explanatory variable i (standards)
bi : weights related to explanatory variable i
\( u \): accidental error

and in a vector expression:

\[
y = b'X + u
\]  \( (5) \)

In which \( x \) is the vector for explanatory variables, and \( b' \) is the transposed the for explanatory variables parameters. As a result:

\[
P(y|x) = b'X
\]

The conditional probability can be interpreted as the probability of approving the credit request which is related to the groups of \( x \) parameters. Therefore, the result of estimating regressions is the estimation of approving new requests. When the decision about granting the loan is made, then the scores gathered should be compared to the threshold limit. It should be mentioned that this model benefits from the fluency of estimation but while in this method some of classic presumptions are broken, then the usage of such method is not very popular. As the result, while the dependant variable has binary values (0 or 1), probit and logit model will have better performance.

**IV. Logit Models**

The conceptual and accounting problems in probable linear models in the above have made the researchers to find other solution. Here, a clear theory exists, and that is the possibility that the estimated probability is placed out of the gap of Zero (0) and one (1), so we have to solve this problem through finding a proper change which guarantees the placement of the estimation between these gaps. Assembled distributing functions can cause a chain of changes which can place \( P \) in (6) equation in the gap between 0 and 1, while it can keep its even characteristic as well. We assume that
logistic distribution has been chosen to say about choosing probability; the logit function will be as follow:

\[ p = \phi(b'x) = \int_{-\infty}^{b'x} \varphi(z)dz = \frac{1}{1 + e^{-b'x}} \]  \hspace{1cm} (6)

Or in a different form:

\[ p = \frac{e^{b_1x_1 + \ldots + b_kx_k}}{1 + e^{b_1x_1 + \ldots + b_kx_k}} \]  \hspace{1cm} (7)

logistic distributing function contrary to normal distributing function has a closed form, therefore it makes logit model’s calculating far easier than probit. As a result, computerizing, executing and usage is relatively cost effective. Because of mentioned benefits and also vast usage of logit model in present study, here we are going to discuss this matter in detail.

Logistic cumulative distribution function:

\[ P_i = E(Y = 1 \mid X_i) = \frac{1}{1 + e^{-(\beta_1 + \beta_2X_i)}} = \frac{1}{1 + e^{-z_i}} \]

\[ P_i = (Y_i = 1 \mid X_i, \beta) = 1 - F(-X'_i\beta), \quad P_i(Y = 0 \mid X_i, \beta) = F(-X'_i\beta) \]

\[ z_i = \beta_1 + \beta_2X_i \]

As \(-\infty < z_i < +\infty\) changes, \(p_i\) changes between 0, and 1 as well. \(p_i\) is related in a non-linear way to \(z_i\). \(p_i\) is non-linear, not only on the basis of \(x\), but also on the basis of \(\beta\). In other words, the ordinary least square method is not applicable in estimating the mentioned model’s parameters. For solving this problem, we can easily change it to linear function on the basis of parameters.

1. **Logit model characteristics:**

1- As "p" Fluctuates between 0 and 1, or in other words "Z" fluctuates between \(-\infty, \infty\), The logit L changes from \(-\infty\) to \(+\infty\).
2- Although “L” on the basis of “X” is linear, the probabilities themselves are not like this. It means that this model is unlike linear probability model in which the probabilities increase in a linear form as “X”.

2. Estimating logit model through using ordinary least square method:
In order to use such method first we have to find the ratio of chance in the mentioned situation:

\[
\frac{P_i}{1-P_i} = \frac{1+e^{z_i}}{1+e^{-z_i}} = e^{z_i}
\]

Then we have to get the (Ln) from it:

\[
L_i = \ln \left( \frac{P_i}{1-P_i} \right) = Z_i = \beta_1 + \beta_2 X_i
\]

Here \( L_i \) should be estimated, but as it is know for some amounts \( L_i \) is equal to 1/0, and in others it is equal to 0/1 which they won’t have any meaning and estimating them through ordinary least square method would be impossible. Therefore, it would be better to categorize the data first and then estimate the probability of each group separately. The mentioned estimation will be as follow:

\[
\hat{P}_i = \frac{n_i}{N_i}
\]

\[
\hat{L}_i = \ln \left( \frac{\hat{P}_i}{1-\hat{P}_i} \right) = \beta_1 + \beta_2 X_i + U_i
\]

If \( N_i \) is sufficiently big and \( X_i \) is distributed independently according to two-phased distribution, then we will have:

\[
U_i \sim N[0, \frac{1}{N_i P_i (1-P_i)}]
\]
Therefore, the interfering parts of logit model have unequal variance and this is exactly the same as linear probability model. It means that we have to use generalized least square instead of ordinary least square.

\[
\sigma^2 = \frac{1}{N_i \hat{P}_i(1 - \hat{P}_i)}
\]

So, if we summarize the stages that should be done, it'll be as follow:

1- To estimate the probability of \( \hat{P}_i = \frac{n_i}{N_i} \) for each Xi.

2- To obtain the logit for each Xi level as follow:

\[
\hat{L}_i = \ln\left(\frac{\hat{P}_i}{1 - \hat{P}_i}\right)
\]

3- Curing the inequality of variance:

\[
\sqrt{W_i L_i} = \beta_1 \sqrt{W_i} + \beta_2 \sqrt{W_i X}, + \sqrt{W_i U}, \tag{8}
\]

\[
L' = \beta_1 X' + \beta_2 X' + V_i
\]

\[
N(p_i)(1 - p_i); W_i
\]

Vi: the Ui of equaled variance.

4- Estimating equation (8) and because it has no width from the matrix, then we can solve it without any matrix width, from the centre.

3. **Estimating logit model by using Maximum Likelihood method**

In order to estimate logit model through ordinary least square method, we will face many difficulties, as the need for categorizing the data. There's a solution for this problem which makes the estimation of such a model easy. This technique is maximum likelihood technique, which is going to be discussed in detail here.
4. Definition of Maximum likelihood

Maximum likelihood function is usually observed as a density function of chain probabilities in random variables, but it is presented as a function of parameter which usually seizes random variable.

Ex:

Suppose that the accidental X can obtain 2 values or a possible amount for example 0, 1. For example consider the result of tossing a coin between 0, 1. Let us suppose "p" has the probability of value 1, and (1-P) has the probability of 0 (Zero).

\[ \Pr(X = 1) = P \]
\[ \Pr(X = 0) = 1 - P \]

Then we can write the density function as follow:

\[ f(X) = P^x (1 - P)^{1-x} \]

And it can be said that

\[ \text{if } X = 1 \Rightarrow f(X) = P, \text{ if } X = 0 \Rightarrow f(X) = 1 - P \]

Suppose that we throw "n" coins and the probability would be head. Now let’s consider Xn as the achievement of throwing the n\textsuperscript{th} coins, and Xn as the achievement of throwing the n\textsuperscript{th} coin.

\[ p_r(X_1 = x_1, \ldots, X_n = x_n; p) = \prod_{i=1}^{n} p^{x_i} \times (1 - p)^{1-x_i} \]
\[ = \frac{n}{\sum x_i} \times \frac{n}{\sum (1-x_i)} \]
\[ = p^{\sum x_i} \times (1 - p)^{n - \sum x_i} \]

Here we need the maximum likelihood estimator, in order to maximize the probability of result.
\[
\max L(x_1, \ldots, x_n; p) = \prod_{i=1}^{n} p^{x_i} (1 - p)^{1-x_i} = \prod_{i=1}^{n} x_i \frac{1}{(1 - p)^{n - \sum_{i=1}^{n} x_i}}
\]

In some cases it would be better to use logarithm instead of Maximum likelihood method. Here to maximum the logarithm function is exactly the same as maximizing the likelihood function itself.

This is because logarithmizing is an even change.

Now here derivation is necessary and we can solve this problem on its basis. In this situation \(P\) is in comparison to:

\[
\ln L = \sum_{i=1}^{n} x_i \ln p + (n - \sum_{i=1}^{n} x_i) \ln (1 - p)
\]

\[
\frac{\partial \ln L}{\partial p} = \frac{1}{p} \sum_{i=1}^{n} x_i + \frac{1}{1 - p} (n - \sum_{i=1}^{n} x_i) = 0
\]

Then we are going to have \(\sum_{i=1}^{n} x_i = Z\) and if we suppose that:

\[
\frac{\partial \ln L}{\partial P} = \frac{1}{P} z - \frac{1}{1 - P} (n - z) = 0
\]

\[
= \frac{(1 - P)z - P(n - z)}{(1 - P)P} = 0
\]

\[
= \frac{z - Pz - Pn + Pz}{(1 - P)(P)} = 0
\]

\[
P_{mle} = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

Here we can conclude that MLE estimator is the same as the average of observations. For example, if number 1 represents tail and number 0 represents head, and 100 coins have been thrown, and out of these 45 heads and 45 tails have been achieved, then the maximum likelihood estimators show 0/45 for the head and 0/55 for observing a tail. Under certain circumstances the
estimators $\beta$ show agreeable maximum likelihood and in case of
limitations they are considered as normal. We can also show that
the estimator is the maximum likelihood, or in other words the
maximum likelihood has the least limited variance among other
normal estimator. On the basis of central limitation theorem if $n$ is
big enough, then we will have:

$$\sigma^2_\hat{\epsilon} = \text{var}(Y_j) = E(Y_j - P_o)^2$$

$$= (1 - P_o)^2 P_o + (P_o)^2 (1 - P_o)$$

$$= P_o (1 - P_o)$$

Which for bigger samples it will be like the following:

$$\frac{\sqrt{n}(P - P_o)}{\sqrt{p_o (1 - p_o)}} \sim N[0, 1]$$

$$2\sqrt{n}(P - 0.5) = \frac{\sqrt{n}(P - 0.5)}{\sqrt{0.5 \times 0.5}} \sim [0, 1] \iff p_o = 0.5$$

5. Estimating logit model:

In logit model $\alpha_o$ and $\beta_o$ are unknown parameter that should
be estimated.

$$P[Y_j = 1 | X_j] = \frac{1}{1 + \exp(-\alpha_o - \beta_o X_j)}$$

$$P[Y_j = 0 | X_j] = \frac{\exp(-\alpha_o - \beta_o X_j)}{1 + \exp(-\alpha_o - \beta_o X_j)}$$

$$F(X) = \frac{1}{1 + \exp(-z)}$$

$$f(Y | X_j, \alpha, \beta) = \left( F(\alpha + \beta X_j) \right)^Y \left( 1 - F(\alpha + \beta X_j) \right)^{1-Y} = \begin{cases} F(\alpha + \beta X_j) & Y = 1 \\ 1 - F(\alpha + \beta X_j) & Y = 0 \end{cases}$$
\[ f(Y \mid X_j, \alpha, \beta) = \left( F(\alpha, \beta, X_j) \right) \left( 1 - F(\alpha, \beta, X_j) \right)^{-1} \]

\[ L_n(\alpha_0, \beta_0) = \prod_{j=1}^n f(y_j \mid X_j, \alpha, \beta) = f(y_j \mid X_1, \alpha, \beta) \cdot f(y_j \mid X_2, \alpha, \beta) \ldots f(y_j \mid X_n, \alpha, \beta) \]

\[ \ln(L_n(\alpha, \beta)) = \sum_{j=1}^n \ln\left( f(Y_j \mid X_j, \alpha, \beta) \right) \]

\[ = \sum_{j=1}^n \left[ Y_j \ln\left( F(\alpha, \beta, X_j) \right) + (1 - Y_j) \ln\left( 1 - F(\alpha, \beta, X_j) \right) \right] \]

\[ = \sum_{j=1}^n Y_j \ln\left( \frac{1}{1 + \exp(-z)} \right) + \sum_{j=1}^n (1 - Y_j) \ln\left( 1 - \frac{1}{1 + \exp(-z)} \right) \]

\[ = -\sum_{j=1}^n Y_j \ln(1 + \exp(-z)) + \sum_{j=1}^n (1 - Y_j) \ln(1 + \exp(-z)) - \sum_{j=1}^n (1 - Y_j) \ln(1 + \exp(-z)) \]

\[ = -\sum_{j=1}^n (1 - Y_j) (Z) - \sum_{j=1}^n (1 - Y_j) \ln(1 + \exp(-z)) \]

\[ = -\sum_{j=1}^n (1 - Y_j) \sum_{i=1}^k \beta_i X_{ij} - \sum_{j=1}^n \ln(1 + \exp(-\sum_{i=1}^k \beta_i X_{ij})) \]

By maximizing this phrase we can estimate \( \beta_i \).

\[ -\sum_{j=1}^n (1 - Y_j) (\alpha + \beta X_j) - \sum_{j=1}^n \ln(1 + \exp(-\alpha - \beta X_j)) = \ln(L_n(\alpha, \beta)) \]

\[ \frac{\partial \ln(L_n(\hat{\alpha}, \hat{\beta}))}{\partial \hat{\alpha}} = -\sum_{j=1}^n (1 - Y_j) + \sum_{j=1}^n \frac{\exp(-\hat{\alpha} - \hat{\beta} X_j)}{1 + \exp(-\hat{\alpha} - \hat{\beta} X_j)} = 0 \] \hspace{1cm} (9)

\[ \frac{\partial \ln(L_n(\hat{\alpha}, \hat{\beta}))}{\partial \hat{\beta}} = -\sum_{j=1}^n (1 - Y_j) X_j + \sum_{j=1}^n \frac{\exp(-\hat{\alpha} - \hat{\beta} X_j)}{1 + \exp(-\hat{\alpha} - \hat{\beta} X_j)} = 0 \] \hspace{1cm} (10)

Then the second derivative should become negative to maximum its phrase and the equations (9) and (10) should be
solved in order to achieve $\alpha$, $\beta$. Such aim is easily possible through using econometrics software's.

*Because of advantages of the logit model, In present study we have used this approach for modeling the credit situation of customers.*

V. Probit Model (Normit):

In probit model we will observe a similar function to logit model but with a difference that instead of using logistic distribution, it uses normal one. While normal distribution is much more complicated than logistic one, probit seems complicated as well, but in reality there is no applicable difference between these two. In probit model the dependant variable ($Y$) is considered as normal distribution and uses normal assembled distribution, in this case $Y$ can choose any number whether positive or negative. Probit function is as follow.

$$P(Y) = \text{cdf}(Y) = \text{cdf}(Y = \alpha + \beta X + \varepsilon) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp\left(-\frac{s^2}{2}\right)ds \quad (11)$$

It should be mentioned that logit and probit model give close results. In the following diagram, the two chosen models, logit and probit, and linear probability are shown.

Figure (4.4): Comparing logit and probit models with discriminate analysis.
VI. Probit model (Normit) and its difference with logit model:

If the dependant variable Y has logistic cumulative distribution, it is called logit, and if the same dependant variable has got normal distribution function, it is called probit or Normit model, which is shown as follow:

\[ P_i = \Pr(y = 1) = \Pr(I_i^* \leq I_i) \]
\[ = F(I_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{I_i} e^{-\frac{t^2}{2}} dt \]
\[ = \frac{1}{\sqrt{2\pi}} \int_{\beta_0 + \beta_1 x_i} e^{-\frac{t^2}{2}} dt \]

In which (t) is the standard normal variable, and in other words has a distribution of t ~ N(0,1). The parameters which have been estimated through logit and probit models are greatly different, but their average derivate are quite close to each other, practically it won't make any difference which model we use, experiment has shown, logit model because of its calculations, is easier to use. In other words the difference between two models is on their shifting function. In logit model, we usually use logistic shifting function and in probit model, Normal shifting function is used. Logistic function in comparison to normal function has a closer shape and from view point of derivatives, it is much easier, and as a result its estimation and calculation would be easier as well. But it should be known that both methods are estimated by a method which has the most probability. In general, the two-phased models are as follow:

1) Linear probability model

\[ P_i = \alpha + \beta X_i \] (12)

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2) Logit model

\[ P_i = \frac{\exp(\alpha + \beta X_i)}{1 + \exp(\alpha + \beta X_i)} \]  \hspace{1cm} (13)

3) Probit model

\[ P_i = \int_{-\infty}^{\alpha + \beta X_i} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt \]  \hspace{1cm} (14)

From experimental point of view, both models show an equal estimation from their derivatives, while cumulative distribution function is different for each model, according to their distribution. Derivatives are different only when enough observation follows their distribution. We can also compare the probit model estimation with the estimation of this model by multiplying logit model by 0.625. On the basis of a study done on the comparison of probit model to logit model, it has been shown that in probit model the limitation of estimated probabilities is between 0.0022 < p < 0.9848, and in the case of logit model the limitations of probabilities is between 0.0059 < p < 0.9765, and in the case of linear probability model the probabilities is between 0/4089<p<1/1931.

4.2.6 Data Spectrum and Variables:

Most of the variables used in credit scoring models are achieved through a number of criteria under the name of LAAP, P5, 6C, which will be discussed in detail.

I. 6C Criteria

This criterion which has been 5C at the beginning and recently another factor has been added to it and has changed to 6C covers the following cases:
• **Character:**

Here character is the applicant’s effort in paying back his loan, which among these characteristics we can mention his truthfulness, and a good reputation. In the case of judging the character of a borrower other items should be inspected too, which are as follow:

- That is, how long it takes for this person to pay his different bills.
- That is, do other loaners and credit institutes have any previous claims from this very person?
- That is, do any of the loaners have ever been obliged to legally follow this person for his debts.
- That is, if the applicant has any bankruptcy background.

• **Capacity:** by using this case, the credit officer, evaluates the financial ability of the applicant for paying back the loan. The loan institute will also inspect the applicant’s monthly salary and his delayed financial obligations. The loan institute will also ask about the applicant’s job, his working background and his income. They will inspect his expenditures and whether this expenditure is supplied from somewhere, or he himself is supplying other people’s expenditure. Another question which would certainly be asked is if the applicant’s income suffices to payback his loan, and in this case the loan holder not only pays attention to the applicants job capacity, but also pays special attention to the applicant’s ability in isolation. This is because the applicant many not work according to his job schedule and therefore won’t have any income, and on the other hand the applicant may have an income separate from his job.
• **Capital:**
  Capital is the net value of the applicant’s wealth. In this case it has been said that the more the applicant’s wealth, the better he can pay his debts back.

• **Collateral:**
  Collateral is a valuable asset that the applicant puts in pledge to guarantee the loan payback, and in the case of any delay it will be confiscated in favor of the bank, so that his debts will be paid back. In the case of big loans, the loan institute can ask for a combination of collaterals.

• **Conditions:**
  This case refers to the general economy conditions which affects the capability of the applicant in the time of payback. The main question about such case is about the applicant’s job security and the company in which he works. The owners of small businesses usually face more problems in receiving a loan rather than the government’s employees.

  One of the reasons that usually the loan institutes give, is that the income of government employees is more trustable than the income of small businesses. Another point is that the loan institutes do not trust the real income of small business owners who may be tempted to present a Fake income, which is much higher than their real income. It is clear that such creative accounts are not wise, while the applicant not only won’t receive the loan requested, but also such person would legally be prosecuted.

• **Condition and terms of loan:**
  This criterion has three major questions:
  - How much credit and facilities does the applicant need?
- For what purpose does the applicant ask for such a loan or credit?
- For how long does the applicant need this loan or credit.

II. LAPP Criteria:

Of other evaluating methods for the applicant’s credit standing is using (LAPP) criteria, which in short contains the following:

- **Liquidity:**
  Liquidity is one of the important factors in the institutes. Sometimes even liquidity is more important than the profit. The cases which will be studied in this part are: the ratio of liquidity to commitments, inspecting the present situation of debts in comparison to capital and the wealth and assets of economic unit, and the combination of their rations.

- **Activity:**
  In this section the kind of activity, its volume, the circulation period of activities and same subjects are being studied and evaluated.

- **Profitability:**
  In this part, the amount of profitability, net profit in comparison to the selling and its finishing price is studied and evaluated.

- **Potentialities:**
  The continuous activity of an economic unit in the market is directly related to its potentialities. Therefore, in this chapter we will discuss and analyze problems such as the situation and efficiency of the management, the combination of man power, products, financial resources, influence on the market and relationship, and other common cases.
III. 5P Criteria:

The other method used in credit studies is 5p method, which is summarized as follow:

- **People:**
  Studying and evaluating people’s ideas about economic units consisting of efficiency in producing, trade, age of managers, profit gained from the capital, and assets, evaluation and control of assets, and tendency toward fulfilling the commitments in industries or economy divisions.

- **Product:**
  To evaluate quality, quantity, profitability, marketing goals, insurance coverage, and etc.

- **Protect:**
  To study this point that whether interior financial protection on the basis of financial statements exits or not. Do liquidity and other securities and deposits exist? Are there any foreign capital protection such as bank guarantee, and financial documents?

- **Payment:**
  Cases such as: Is there the problem of default credits? Studying information related to previous payments, liquidity capability, profitability, quality, foreign debts, and etc.

- **Perspective:**
  To study this point that whether the company has any plans or strategies for the future? Or is it a beginner in its work?
  To study the profit of sells, market possibilities in the face of price’s fluctuation. By studying and evaluating the above mentioned criteria, the credit decision makers will be able to
give their opinions about granting loans and credits, credit ceiling and ways of controlling it, and also the time and conditions of repayments. *In present study we have used the 6C criteria to collect necessary data for credit scoring model.*

**IV. Data Sampling:**

Our statistical sample is a number of 500 customers of *Post bank of Iran*, which have been chosen as a cluster sample from different areas in Iran. Among these customers, the ones whose information is either incomplete or completely out of defined limits of this study have been omitted. Among these, a number of 400 files have been chosen for making a logit model.

The variables used in this research are as follow:

- **x1**: Average amount of current account in the last 6 month
- **X2**: having Outstanding Loan [have (1), don't have (0)]
- **x3**: number of years working with banking system
- **x4**: logarithm of total loan being granted before.
- **x5**: kind of securities or collateral [mortgage document (0), others (1)]

**Y1**: The dependant variable which has the amount of (0) to (1), (1) is the defaulted and (0) is the none defaulted.

**4.2.7 Estimation of model:**

Logit model is a regression technique, in which the dependant variable is a permanent on which chooses the amount of 0 to 1, and the logistic distribution variable is also as follow:

\[ Y_i = \begin{cases} 1 \\ \infty \end{cases} \]
As we can observe \( P(y = 1|x) \) is not dependent on logistic dependent coefficient in a linear way, therefore in order to maximize the probability of the observed data we have to use maximum likelihood method instead of ordinary least square.

\[
P(Y = 1|X) = \frac{1}{1 + e^{-\left(b_0 + b_1 X_1 + \ldots + b_k X_k\right)}}
\]

In order to make logit models and in order to choose variables a stepwise method has to be used. The stepwise method is done for choosing variables on the meaningful statistic basis which studies the importance of variables as well; this method can either enter them into the model or extract them from it. Finally, we have prepared a model for our legal customers which processes are as follows:

Table (4.1): Estimation of logit model by using of Eviews Software

<table>
<thead>
<tr>
<th>Estimation Command:</th>
</tr>
</thead>
<tbody>
<tr>
<td>BINARY (D=L) P C MCU TC TT SF CO</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimation Equation:</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 1-@LOGIT((-C(1) + C(2)*MCU + C(3)*TC + C(4)*TT + C(5)*SF + C(6)*CO))</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Substituted Coefficients:</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 1-@LOGIT((-0.06519253786 - 2.365725268<em>MCU + 3.081263388</em>TC - 0.09807636054<em>TT + 0.1214929986</em>SF + 1.068573229*CO))</td>
</tr>
</tbody>
</table>
Dependent Variable: P
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 10/03/08 Time: 02:21
Sample: 1 400
Included observations: 400
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.065193</td>
<td>0.473005</td>
<td>-0.137826</td>
<td>0.8904</td>
</tr>
<tr>
<td>MCU</td>
<td>-2.365725</td>
<td>0.355854</td>
<td>-6.648016</td>
<td>0.0000</td>
</tr>
<tr>
<td>TC</td>
<td>3.081263</td>
<td>0.328883</td>
<td>9.368873</td>
<td>0.0000</td>
</tr>
<tr>
<td>TT</td>
<td>-0.098076</td>
<td>0.031823</td>
<td>-3.08196</td>
<td>0.0021</td>
</tr>
<tr>
<td>SF</td>
<td>0.121493</td>
<td>0.057062</td>
<td>2.129154</td>
<td>0.0332</td>
</tr>
<tr>
<td>CQ</td>
<td>1.068573</td>
<td>0.324506</td>
<td>3.292923</td>
<td>0.0010</td>
</tr>
<tr>
<td>Mean dependent var</td>
<td>0.490000</td>
<td>S.D. dependent var</td>
<td>0.500526</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.329413</td>
<td>Akaike info criterion</td>
<td>0.724404</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>42.75407</td>
<td>Schwarz criterion</td>
<td>0.784276</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-138.8807</td>
<td>Hannan-Quinn criter.</td>
<td>0.748114</td>
<td></td>
</tr>
<tr>
<td>Restr. log likelihood</td>
<td>-277.1789</td>
<td>Avg. log likelihood</td>
<td>-0.347202</td>
<td></td>
</tr>
<tr>
<td>LR statistic (5 df)</td>
<td>276.5963</td>
<td>McFadden R-squared</td>
<td>0.498949</td>
<td></td>
</tr>
<tr>
<td>Probability(LR stat)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs with Dep=0</td>
<td>204</td>
<td>Total obs</td>
<td>400</td>
<td></td>
</tr>
<tr>
<td>Obs with Dep=1</td>
<td>196</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

So, estimated equation is as follow:

\[
P(Y=1|X) = \frac{1}{1+e^{-(-0.065-2.366X_1+3.08X_2-0.098X_3+0.121X_4+1.068X_5)}}
\]

4.2.8 Accuracy tests of estimated model:

I. McFadden R-squared

McFadden's R2 statistic is a follow:

\[
Mc - fadden's - R^2 = 1 - \left[ \frac{LL(\alpha, \beta)}{LL(\alpha)} \right]
\]

The R2 statistic is a scalar amount between 0, and 1 which in linear probability model is close to 1.
Value of This criterion for our regression is 0.49 which shows that our estimation has been done properly.

II. Z-Statistic:

The meaningfulness of each regression coefficients is studied by statistics Z. By studying prop Z, the description of coefficient’s value is kneaded with this reality that, the estimated coefficients of binary models can not be described as the final effect on dependant variable.

The study of variable’s marginal effect and the final effect of Xi on conditional probability is estimated as follow:

\[
\frac{\partial t(Y|X_i, \beta)}{\partial X_i} = f(-X'\beta|\beta_j)
\]

And the coefficient sign shows the direction of related variable’s effect. For example, the negative sign shows that the increase in our variable will cause a decrease in the probability.

As it has been shown in table (4.2), all of Z- statistics for model’s variable are higher than value 2. By considering meaningfulness level of 5%, all of coefficients are meaningful and acceptable.

III. Value and probability of LR-Statistic:

This test is completely similar to statistics F in linear regression models, and it tests the general meaningfulness of the regression, in a way that it tests the theory of absence of \( \beta_i \) for the regression coefficient except the width of the matrix which is estimated as \(-2(\bar{L} - L)\). The number in the parenthesis in front of this statistic is the indicator of the degree of freedom which is indeed the same number of restrictions under testing. It should be mentioned that this test has no
efficiency in the worthless matrix. The ratio of likelihood in (LR) model is as follow:

\[
LR[-i] = -2[LL(\alpha) - LL(\alpha, \beta)] \\
LR[-i] = \{-2LL(old\ model)\} - \{-2LL(new\ model)\}
\]

LR with X2 has been distributed by “1” degree of freedom, which “i” stands for both the independent variables.

In other words, in order to do the test for absence theory for the entire regression, there are two ways:

\[
H_0 : \beta_i = 0, \beta_i = 0, \ldots, \beta_m = 0 \\
m < k
\]

One of them is related to test F, Which estimates the logit model again, and according to the theory of absence, which is as follow:

\[
\ln(L_n(\hat{\beta}_1, \ldots, \hat{\beta}_m)) = \max \ln(L_n(\hat{\beta}_1, \ldots, \hat{\beta}_k))
\]

And then the log-likelihood comparison takes place

The second method of testing is called ratio of likelihood, which under the theory of absence and for bigger samples are as follow:

\[
LR_m = -2 \ln \left( \frac{L_n(\hat{\beta}_1, \ldots, \hat{\beta}_k)}{L_n(\hat{\beta}_1, \ldots, \hat{\beta}_k)} \right) \sim \chi^2_m
\]

As it has been shown in table (4.2), value of this statistic is **276.6** and probability of LR is **zero (0.0000)**. As a result the theory of absence is meaningless for the whole regression, or in other words the regression itself is meaningful.
IV. First Kind and Second Kind Error calculation:

The exit of logit model is between 0, and 1. In order to determine whose received facilities in future will be defaulted and whose will be liquidated, We need a threshold. Here it should be clear that if the logit probabilities are placed lower than the customer, he will be categorized in the group of ideal customer, and if these probabilities are higher than this threshold, then he will be placed in the opposite. On the basis of this categorizing rule that the customers are placed in two different groups, we will face two errors. It means that we can easily categorize an applicant whose facilities are supposed to be liquidated and will be placed in the group of ideal customers or vice versa. Therefore, for predicting such problem we should measure the binary error. For example, suppose we have 10 high risk applicants, but when we observe the results of the model, we will understand that instead of 10, we’ve got 20; here is when we have made mistakes in categorizing the customers in wrong places. Therefore considering this error in our decision making we will have:

**Error type 1 (Credit risk):** means the placement of high risk applicants in the opposite group.

**Error type 2 (Commercial risk):** means the placement of ideal applicants in the opposite group.

But the threshold of categorizing the people into these two groups should be studied carefully. This threshold should be determined in such a way, that the error threshold reaches to its minimum. Every and each of these errors has costs for the bank, which categorizing high risk customers in the opposite group will have worse follow ups. Whereas the costs of error no.1 for example contain legal prosecution costs, costs of losing the principal money and its interests, and the cost of error no.2 for
example contain loosing the margin of the money, which quantifying these two costs is really difficult, so for determining the threshold limit the general cost function should be minimized:

The expected Cost:

$$EC = \pi_{fal} C_{type\ I\ TypeI} + \pi_{top} C_{type\ II\ TypeII}$$

*C type I: Costs of error type 1
*C type II: costs of error type 2
*\pi_{fal}: the share of bad customers
*\pi_{top}: the share of good customers

Stata software can easily do this job by minimizing the error and gives us the threshold limit. This has been mentioned in figure (4.5). In the figure we have two expressions: *Specificity*, and, *Sensitivity* which by these two they mean error type 1 and error type 2. In the case of our model the threshold limit of 0.5 has been obtained.

Figure (4.5): Stata output for determining threshold limit
V. Misclassification Matrix

To test the accuracy of a model from its functional point of view there are different methods.

The main tests are "Misclassification matrix" and "Roc curve". These matrix and curve can be calculated by "Sata" and "Eviews" software. The complete result of misclassification matrix has been mentioned below.

Table (4.3): Stata output for misclassification Matrix of logistic model

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
\textbf{Classified} & \textbf{D} & \textbf{~D} & \textbf{Total} \\
\hline
+ & 169 & 30 & 199 \\
- & 27 & 174 & 201 \\
\hline
\textbf{Total} & 196 & 204 & 400 \\
\hline
\end{tabular}
\caption{Logistic model for y}
\end{table}

Classified + if predicted \( Pr(D) \geq 0.5 \)

True D defined as \( y = 0 \)

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity ( Pr(+</td>
<td>D) )</td>
</tr>
<tr>
<td>Specificity ( Pr(-</td>
<td>\sim D) )</td>
</tr>
<tr>
<td>Positive predictive value ( Pr(D</td>
<td>+) )</td>
</tr>
<tr>
<td>Negative predictive value ( Pr(\sim D</td>
<td>-) )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>False + rate for true ( \sim D ) ( Pr(+</td>
<td>\sim D) )</td>
</tr>
<tr>
<td>False - rate for true D ( Pr(-</td>
<td>D) )</td>
</tr>
<tr>
<td>False + rate for classified + ( Pr(\sim D</td>
<td>+) )</td>
</tr>
<tr>
<td>False - rate for classified - ( Pr(D</td>
<td>-) )</td>
</tr>
</tbody>
</table>

Correctly classified \( 85.75\% \)
First part of output is as below:

<table>
<thead>
<tr>
<th>Legal customers</th>
<th>Actual Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast result</td>
<td>Good  Bad</td>
</tr>
<tr>
<td>B=30 A=169</td>
<td>Bad</td>
</tr>
<tr>
<td>D=174 C=27</td>
<td>Good</td>
</tr>
</tbody>
</table>

In the above table the results achieved have been deduced from comparison with the actual result.

**Section A:**
In this section there are a number of files which the facilities are in default. The model is also categorized as defaulted in this part.

**Section B:**
This section contains files in which the facilities or loans are settled and their models have been classified under “out standing loans”.

**Section C:**
This section contains files in which the facilities or loan are not settled and their models have been classified under “settled”.

**Section D:**
This section contains files in which the facilities and their models are both classified under “settled”.

\[
0.137 = \frac{C}{C + A} = \frac{27}{27 + 169} = \frac{27}{196} = \text{credit risk (error type 1)} = (1-\text{sensitivity})
\]

\[
0.147 = \frac{B}{B + D} = \frac{30}{30 + 174} = \frac{30}{204} = \text{commercial risks (error type 2)} = (1- \text{Specificity})
\]
VI. ROC CURVE (Receive operating classification curve)

One of criteria used in classification of the models is "Roc curve". In order to find out which debts are going to be outstanding and which ones will be settled, we need to find the value for the limit of threshold "C".

Any debtor that his or her score or probability of default is more than the value of "C", will be classified under "outstanding" and vice versa. This is to say that if the probability of default is more than "threshold limits", and if the future trend would be the same, therefore, we can assume the classification has been done correctly.

\[
HR(C) = \frac{H(C)}{ND} = \frac{\text{Number of the files that the have been caterbrier in high risk group}}{\text{All past due}}
\]

\[
FAR(C) = \frac{F(C)}{N_{ND}} = \frac{\text{Number of files that the have been settled and put in ideal customer group}}{\text{All the default}}
\]

The minus level of ROC is defined as below:

\[
AUC = \int_0^1 HR(FAR)d(FAR)
\]

If one model with the classification power of "0", the "area" under "Roc" curve of "0.5" and the best area under curve of it is "1.0", the area level for our model has been calculated as "0.93". figure shows the ROC curve for our model as below.
4.2.9 Establishing credit groups and ranking the customers:

As we have mentioned before, in this stage we have to create the ranking system and placing the customers in their related credit groups.

In order to rank the credit of customers, there are many agencies that have the ability to do such work.

To name a few of these agencies, we can introduce:

- Fitch ranking institute
- Modeey’s ranking institute
- Standard And poor (SandP) ranking standard institute
- Banks, and other ranking institutes

In which each of the above mentioned institutes have special criterion for different credit groups. (See table (4.4)).
Table (4.4): Credit ranking structure of moody’s, SandP, and Fitch

<table>
<thead>
<tr>
<th>Ranking definition</th>
<th>Moody’s</th>
<th>S and P</th>
<th>Fitch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest credit ranking</td>
<td>Aaa</td>
<td>AAA</td>
<td>AAA</td>
</tr>
<tr>
<td>Very high credit ranking</td>
<td>Aa1</td>
<td>AA-</td>
<td>AA-</td>
</tr>
<tr>
<td></td>
<td>Aa2</td>
<td>AA</td>
<td>AA</td>
</tr>
<tr>
<td></td>
<td>Aa3</td>
<td>AA-</td>
<td>AA-</td>
</tr>
<tr>
<td>High credit ranking</td>
<td>A1</td>
<td>A-</td>
<td>A-</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>A</td>
<td>A</td>
</tr>
<tr>
<td></td>
<td>A3</td>
<td>A-</td>
<td>A-</td>
</tr>
<tr>
<td>Good credit ranking</td>
<td>Baa1</td>
<td>BBB+</td>
<td>BBB+</td>
</tr>
<tr>
<td></td>
<td>Baa2</td>
<td>BBB</td>
<td>BBB</td>
</tr>
<tr>
<td></td>
<td>Baa3</td>
<td>BBB-</td>
<td>BBB-</td>
</tr>
<tr>
<td>Trading credit ranking</td>
<td>Ba1</td>
<td>BB+</td>
<td>BB+</td>
</tr>
<tr>
<td></td>
<td>Ba2</td>
<td>BB</td>
<td>BB</td>
</tr>
<tr>
<td></td>
<td>Ba3</td>
<td>BB-</td>
<td>BB-</td>
</tr>
<tr>
<td>Very High trading credit ranking</td>
<td>B1</td>
<td>B+</td>
<td>B+</td>
</tr>
<tr>
<td></td>
<td>B2</td>
<td>B</td>
<td>B</td>
</tr>
<tr>
<td></td>
<td>B3</td>
<td>B</td>
<td>B</td>
</tr>
<tr>
<td>High risk ranking due to negligence</td>
<td>Caa1</td>
<td>CCC+</td>
<td>CCC</td>
</tr>
<tr>
<td></td>
<td>Caa2</td>
<td>CCC</td>
<td>CC</td>
</tr>
<tr>
<td></td>
<td>Caa3</td>
<td>CCC-</td>
<td>C</td>
</tr>
<tr>
<td>Negligence ranks</td>
<td>Ca-C</td>
<td>CC</td>
<td>DDD</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C</td>
<td>DD</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D</td>
<td>D</td>
</tr>
</tbody>
</table>

Lack of financial data of real customers (applicants) and their undeniable share of the banking credits, non-discloser of financial data by companies, improper auditing and falsified
accounts by companies are all reasons for not using the financial data.

"Logit function" mentioned above is an indicator that the function of the facilitation is going to be defaulted.

In this way if the probability "(p(0))" is close to "one" the probability of credit defaults is higher and vice versa.

The applicants and bank customers under "logit model" are categorized as below:

Table (4.5): Credit ranking of Post Bank Iran’s customers

<table>
<thead>
<tr>
<th>Description</th>
<th>Distance of the Limit of probability P(0)</th>
<th>Abundance “F”</th>
<th>percentage</th>
<th>category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very good applicants/customer</td>
<td>0.0 – 0.02</td>
<td>22372</td>
<td>14.1%</td>
<td>A +</td>
</tr>
<tr>
<td>Good Applicants/customer</td>
<td>0.021–0.04</td>
<td>70562</td>
<td>44.5%</td>
<td>A</td>
</tr>
<tr>
<td>Average Applicants/customer</td>
<td>0.041–0.06</td>
<td>36396</td>
<td>22.9%</td>
<td>B</td>
</tr>
<tr>
<td>High risk Applicants/customer</td>
<td>0.061–0.08</td>
<td>17264</td>
<td>10.9%</td>
<td>C</td>
</tr>
<tr>
<td>Unacceptable Applicants/customer (Always default)</td>
<td>0.08–1</td>
<td>12049</td>
<td>7.6%</td>
<td>D</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>158643</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>
4.3 Exposure limits determination

In this section we shall try to first describe the present situation “The process of defining exposure limits of credit pillars” In “Post Bank of Iran” as a pilot or test subject and we shall also refer to the status of certain other commercial banks in this regard.

Our aim is to create a scientific model to define the exposure limits of credit pillars (authorities) according to the risks involved. Since defining these limits can actually affect the intensity of the exiting flow of resources, and at the same time influence the establishment of credit risk and value at risk, it is considered of the outmost importance.

One should note that in banking operations “exposure limits” are in no way used to curtail the loan facilities. The aim is to make “exposure limits” and “method of credit operations” of credit pillars compatible.

Applying control and risk related management and also optimizing the use of resources are also a part of this process.

4.3.1 Method of calculating the exposure limits in Iranian Banks:

Credit department of each bank is one of the most important sections of any bank. The function of this department in credit risks, value at risk and their risk management methods play an important role in the system.

The system governing over various commercial banks' credit department is that in accordance with different facilities and commitments provided for different legal and real entities, all branches and supervisory are ranked, and the exposure limits of credit pillars for providing these facilities are calculated on the basis of each facility (per one unit).
To reach these limits additional factors like deposit targets, the exposure limits of the credit pillars of other banks and other internal credit policies should be taken into consideration.

I. Post bank of Iran

As the authority of the banks and ceiling of the credit budget are only in the area of Islamic contracts, and other policies are dictated by the central bank of Iran, therefore, only the Islamic contracts will be discussed throughout this text.

In present condition the authorities of the committees are not compatible with the amount of their credit risk, and usually are in accordance to with the amount of resources (deposit target) and the risk of their banks.

By dividing the provinces into five levels in the order of which one has reached the deposit targets (resources), their authority limits are determined. For example the provinces that they rank “one” in comparison with the provinces which are ranked “Five”, have three times more authorities. On the other hand, the authority limits in the two areas of Real and Legal customers are categorized in a way that the ratio of real persons to legal person is %20 in the same rank or level.

II. Sepah Bank

Up to the year 2005 the authority limits of credit pillars were determined by a table in which districts were divided into three areas with rankings 1, 2 and 3. But in 2006 this authority was turned to the districts themselves and eventually they were the ones which ranked the branches. The reason behind this decision was that the management had reached a point in which they had a clear knowledge and perception over their districts branches.

In this way the districts will function with more independence. The changes in the limits of authorities in “Sepah Bank” has not been directly in place because of macro-economics factors like inflation,
and the internal policies for income and credit targets have also had the real effect.

III. Mellat Bank

The figures in the table of authority limits for credit pillars are all derived from the basic methods and internal policies of mellat bank.

These figures are derived with respect to the general and overall situations of the facilities throughout the bank, by utilizing statistical methods and finally they are analyzed and posted. In other word these figures are the feedbacks received from the overall statistics in relation to various facilities and loans. Some of the criterions used like, Guidelines, internal memorandums and related authorities, statues of various facilities and deposits (Resources) all have influence on the exposure limits of credit pillars.

Decisions in relation with determination of these figures (from the view point of the facilities and commitments and ranking the credit pillars) are made by a council consisting of credit and districts management, specialists and banking theoreticians.

IV. Bank Melli Iran

Bank Melli Iran changes the exposure limits of its credit pillars every two to three years in accordance with the needs and internal policies of the bank. In the 1st phase divisions are assumed with regards to volume of activities and the condition of different areas. These are then put into different categories. Then an inquiry takes place in order to find out the extent of their required resources and exposure limits for each branch, district or area. The results are reviewed by experts to find the right and most logical requirements. The final results are declared in the form of a table to all levels for implementation. In action, if the request for review and evaluation of the customers facilities from higher pillars increases, then in order to avoid overloading the higher pillars with work, the exposure limits of
that particular area will be increased and additional staff will be provided to help the above mentioned area.

In Bank Melli Iran the emphasis is placed the expertise and knowledge of the people which rectify the facilities in the various credit pillars. In general, the limits of exposure of credit pillars are determined centrally, but these limits are not the same for different regions (districts), cities and branches of equal standing.

V. Tejarat Bank

In this bank the exposure limits of credit pillar are defined in accordance with to the overall status of the facilities, memorandums, internal regulations and related authorities, and the forecasting of the cash flow (value at risk) which can be collected.

In other words the exposure limits of the credit pillars are usually in accordance with to the internal criterion which will be supplied by the directorate of credit and credit affairs’ Management.

4.3.2 Existing difficulties of the present method:

Some of the existing difficulties in the present system of determining exposure limits are as follow:

I. The variance in the exposure limits of the credit pillars for all kinds of facilities and obligations are not derived in accordance with the risks involved.

II. The exposure limits of credit pillars in granting facilities are not related to the past performance and the risk capacity (volume).

III. Derivation and changes of the exposure limits do not have the necessary scientific basis. Therefore, the process of calculation and evaluation of credit pillars’ performances in indexes have become troublesome, in a way that the accurate evaluation of performances of credit pillars and rectification the probable variances are not possible. So it will be the cause of progressive
increases in the amount of credit risk and naturally the existence of the bank itself would be threatened.

IV. Determining the exposure limits of the credit pillars are usually based on the internal policies of the banks and not the dynamics of the basic parameters and macro-economic dimensions. The combination of these factors has put the banks in great risks in order to render facilities. These figures of defaults are so great and the actual amount is much higher than the figures forecasted or estimated.

Therefore, it is needed that the limits of credit pillars in the case of granting facilities, whether according to contracts’ separation or the separation of branches, should be determined on the basis of their previous functions, and the degree of the imposed risk. In this case, granting facilities to the activities with high risk (unessential) will be reduced, and on the other hand, the authority of grating pillar facilities, which have never had a desirable background in the case of granting facilities, and have always risked the banks resources will be reduced proportionally, and will provide the suitable ground for exercising credit risk management.

4.3.3 The theoretical basis of determining exposure limits:

Generally, the exposure limits of credit pillars are determined through the inner bank information and data’s, and its aim is to determine a ceiling for all kinds of facilities. Therefore, by considering “the general definition of systems”, the “process of exposure limits of credit pillars” itself is an informational system.

I. Dynamic and open system: As it has been defined, this system is constantly receiving its needed information from internal or external environment, and after processing and changing their forms, will return them.
II. The adapting mechanism (dynamic and stable)

This system should simultaneously have two different mechanisms in order to make a balance between the environments and the situation of the system. This system is consisted of different parts and their sub-system. This means that it will prevent the swift change of sub-system in the face of accidental changes or environmental shocks in a way that it endangers the whole system. This is called "the factor of tendency towards stability".

On the other hand, while the system is activated in an environment that is constantly changing, therefore it should have a mechanism in order to distinguish the aforementioned changes, and adapt itself to them, to achieve a dynamic balance. This is called “the factor of tendency towards dynamism”. Such balance is usually achieved through learning from information feedbacks, and the growing of organizations' internal subsystems.

III. The necessity of feedback existence in the systems for correcting, controlling, and managing them

This subject is so important that the non-existence of feedback will cause an increase of system internal disorder, and finally cause its declination and destruction while these feedbacks will shift the declinations and derivation from the main course to the system. And by giving this information the deviation and difficulties will be modified. Therefore to receive the relate data from the function of the system from it's environment, on should design the most logical methods & Process.

By considering what has been mentioned, it seems that the P.B.I’s system of determining the exposure limits of credit pillars should be based upon the items mentioned below:

- Compiling the necessary standards in order to present an agreeable model.
- Designing a receiving unit and a processor of system outlets (output).
• Designing and evaluating unit of outlets according to the standard, and measures.
• Designing a functional and performable unit.

By predicting the aforementioned parts in controlling units, we will create a cybernetic system, which in itself is a system of feedback, and appropriate control. The topics above can be shown in figure (4.7).

Figure (4.7): Cybernetic System Futures

In this part some faults can be observed in outputs related to inputs, or the process, and finally the system functions, which will result in an improper output.

Unless there is a proper relationship between “function”, and “correcting the functional error” in a bank’s credit pillars system, or the feedback will be transferred with a delay, we should not expect a proper function from them.

In the case of using the feedbacks in the P.B.I’s granting facilities system, we should first define a limit or standard to evaluate the function of granting units, and then compare the real function of different units to these limits and standards. By using the information existing in these feedbacks, we can correct the possible declinations. For example if the amount of credit risk, or if the possibility of
postponing the facilities granted has exceeded the permissible limit, then it should be considered as no agreeable incident, and an immediate action should be taken in order to reduce it. If this ratio was acceptable for one unit, then their function should be accepted as well, and should be encouraged to continue and improve the existing trend.

4.3.4 Proposed Model for determining the exposure limits:

It may be said that the most proper method for determining the exposure limits of credit pillars is the relationship between this limit and the bank’s internal and external effective factors. For example, from the external factors the following could be mentioned: cash volume, inflation, government policies or other banks’ trends. From the internal factors we can mention the functional method and the rate of risk formed by any of the credit pillars, memorandums and the bank’s credit directions.

Therefore, by recognizing the effective internal and external factors on credit risks, we can relate the attached fundamental factors to the determined exposure limits of credit pillars through designing a new model, then we can be optimistic that determining this exposure limits can have logical results, while it benefits from scientific backings. This can control the operational risk and prevent those with unnecessary risk. By taking the role of related factors to credit risk into consideration we can have a brief description which will be as follow:

I. Credit risk index:

This is considered as one of the most effective factors on credit subjects. Credit risk is the customer’s probable incapability or his desire for not paying back the facilities received which consists of the principal and interest of the sum, or in other words it is the possibility
of postponing the granting facilities. As we mentioned in last section by details, this possibility is estimated from the logit model, which can be interpreted as follow:

\[ p(y | x) = \varphi(b'x) = \int_{-\infty}^{\infty} n(z) dz = \frac{1}{1 + e^{-b'x}} = \frac{e^{b'x}}{1 + e^{b'x}} \]

\( X: \text{The independent variables and factors} \)
\( b: \text{The coefficient of independent variables} \)
\( p(0): \text{The postponing, (default) probability} \)

The output of the logit model is considered as the customers risk balance, and it is perfectly clear that in order to reduce the credit risk, the amount of the facilities should be reduced proportionate to the risk increase.

Here the credit measuring model acts as the stability and amortization or depreciation error in the exposure limit model. In each of the credit pillars domain we can use the average of restraining rate of customers, especially those which have been extracted from logit model.

\[ P_i = \mu_i = \sum p_i, j / n_j \]

\( i: \text{Each category (every and each of the credit pillars)} \)
\( j: \text{the number of the credit customers in each of the categories}. \)

Because of the existence of %2 standards for the credit risks in each of the bank’s units, we can explain the following relationship for the risk index of \( p \leq 0.02 \) as follow:

\[ p = \left\{ \begin{array}{ll}
  p > 0.02, & 1-p \\
  p \leq 0.02, & 1.02 - p
\end{array} \right. \]

In other words if the average of the restraining (default) rate is equal to %2 then, it will not have any effect on the changes of the exposure limits, and for less than that, it will cause an increase in the limits of its pillars.
II. Inflation rate:

It can be said that the inflation rate is one of the most effective variables on the macro-economic dimensions, which can have influence on most of real aspects of economic activities. It also has a reducing effect on the credit and value of the country’s currency. This will cause a decrease in the purchasing power of money unit in the length of time; therefore it has a reducing effect on the exposure limit of credit pillars which is stable and also in money unit.

In order to compensate the decrease in purchasing power of facilities’ receivers, these limits should be increased with the same amount of inflation rate in a way that the purchasing power of the bank’s credit customer will at least be supplemented as the previous year.

It seems logical that the authorized limit of risk formation and restraining rate of the facilities in a bank can at most be equal to the efficient rate of the facilities, and under no circumstances, any of the credit pillars can take an action which its risk is more than the facilities paid. While, no risk should ever be imposed to the customers fixed deposit in a bank. Therefore the red line for each of the credit pillars will at most be equal to the effective rate of the facilities. In other words, if the restraining of a credit pillar reaches the effective rate, then no more facilities will be granted. On this basis, and in order to simulate the nature of risk to the nature of facilities, we can consider the effective rate of the facilities as a \( (b) \) coefficient.

If the following coefficient is divided to the credit restraining rate \( (i) \) and the result is deducted from 1, then we will achieve the \textit{regulating index} of choosing granting facilities in credit pillars “i” as follow:

\[
\rho_i = 1 - \frac{p_i}{b}
\]
In this model, the percentage of the bank’s resources growth, which is greatly affected from the increase in cash volume in the economy, has replaced the inflation rate. From the systematic view point, the inflation rate or resources growth affected from the cash flow can act as the dynamic factor in the model of exposure limit, while it always causes an increase in exposure limit in each period of time. Therefore, because of its increasing effect the related index can be shown as follow:

\[ G = (1 + g_{di}) \]

In this way, in the considered model both of the stability factors (risk index) and dynamic one (inflation rate or resources growth) is attended.

4.3.5 Compiling a model for the exposure limits:

By considering the risk of credit customers in each area and the inflation rate, and also considering the competition between banks and the percentage of its proportion with the bank’s resources, the mentioned model can be as follow:

\[ a_t = (1 - \frac{p_i}{b}) \ast (1 + g_{di}) a_p \]

\[ \phi = (1 - \frac{p_i}{b}) \ast (1 + g_{di}) \]

\[ a_{\hat{z}} = \phi a_p \]

The above mentioned can be explained in an expanded format as well:

\[ A(I,j)_t = \phi(i,j)_t - 1 \times a(i,j)_t - 1 \]

\[
\begin{bmatrix}
  a(1,1)_t & a(1,m)_t \\
  \vdots & \vdots \\
  a(n-1,t) & a(n,m)_t
\end{bmatrix}
\times
\begin{bmatrix}
  \phi(1,1)t-1 & \phi(1,m)t-1 \\
  \vdots & \vdots \\
  \phi(n,1)t-1 & \phi(n,m)t-1
\end{bmatrix}
\times
\begin{bmatrix}
  a(1,1)_{t-1} & a(1,m)_{t-1} \\
  \vdots & \vdots \\
  a(n,1)_{t-1} & a(n,m)_{t-1}
\end{bmatrix}
\]

In the above mentioned:
\( I = 1, \ldots, n \) \( j = 1, \ldots, m \)

\( a_t: \) the current year matrix of exposure limits for “n” Credit pillar, and “m” kind of contract.

\( a_o: \) The previous year matrix of exposure limits for n credit pillar, and m kind of contract.

\( P_i: \) The credit risk index of credit pillars i

\( g_{di}: \) The degree of credit pillar resources growth i

\( \phi: \) Coefficient matrix

As it is clear, the exposure limit is determined for the period of one year time, and on the basis of the previous year function. Therefore, it can be shown as follow:

\[ a_t = \phi a_o \]

\[ a_t = \phi a_{t-1} \]

\[ a_t - \phi a_{t-1} = 0 \]

The above mentioned forms are non-linear differential equations which their answers are:

\[ a_t = a_o \phi_i \]

This shows the dependence of the new limits in each period of time to the matrix of basic exposure limits \((a_0)\), and the degree of coefficient matrix \((\phi)\).

The above model is compiled with the aim of controlling the credit activities risk of internal units in a bank. It means that by increasing the delayed claims, and past due dates, and decrease in achieved points, the degree of the exposure limits decreases as well.

It should also be mentioned that the inflation, and the percentage of the resources growth, are two external factors which are out of the control of the internal units in a bank.

Table (4.6) shows the result of determined exposure limits for PBIs’ credit pillars.
Table (4.6) The result of determined exposure limits for PBIs' credit pillars

<table>
<thead>
<tr>
<th>Credit Pillars</th>
<th>probability of default</th>
<th>PD deflator</th>
<th>Resource growth rate</th>
<th>Correction coefficient</th>
<th>Initial exposure limit</th>
<th>New exposure limit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>commercial loan</td>
<td>personal loan</td>
</tr>
<tr>
<td>Azar-shargi</td>
<td>5.3%</td>
<td>0.79</td>
<td>77%</td>
<td>1.40</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Azar-gharbi</td>
<td>34.0%</td>
<td>0.71</td>
<td>104%</td>
<td>1.45</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Ardebil</td>
<td>2.7%</td>
<td>0.60</td>
<td>99%</td>
<td>1.20</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Esfahan</td>
<td>3.8%</td>
<td>0.51</td>
<td>159%</td>
<td>1.32</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Ilam</td>
<td>5.2%</td>
<td>0.59</td>
<td>34%</td>
<td>0.79</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Boushehr</td>
<td>6.4%</td>
<td>0.22</td>
<td>116%</td>
<td>0.47</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Chahar mahal</td>
<td>5.3%</td>
<td>0.75</td>
<td>111%</td>
<td>1.59</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Khorasan jonobi</td>
<td>10.2%</td>
<td>0.88</td>
<td>206%</td>
<td>3.07</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Khorasan razavi</td>
<td>3.2%</td>
<td>0.66</td>
<td>214%</td>
<td>2.07</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Khorasan shomali</td>
<td>1.6%</td>
<td>0.81</td>
<td>222%</td>
<td>2.60</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Khozestan</td>
<td>4.4%</td>
<td>0.33</td>
<td>85%</td>
<td>0.61</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Zanjan</td>
<td>2.5%</td>
<td>0.96</td>
<td>113%</td>
<td>2.16</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Tehran-South</td>
<td>8.7%</td>
<td>0.79</td>
<td>301%</td>
<td>3.18</td>
<td>2,500</td>
<td>500</td>
</tr>
<tr>
<td>Tehran-North</td>
<td>0.5%</td>
<td>0.85</td>
<td>77%</td>
<td>1.77</td>
<td>2,500</td>
<td>500</td>
</tr>
<tr>
<td>Tehran-Center</td>
<td>2.7%</td>
<td>0.81</td>
<td>198%</td>
<td>2.41</td>
<td>2,500</td>
<td>500</td>
</tr>
<tr>
<td>Semnan</td>
<td>2.0%</td>
<td>0.81</td>
<td>181%</td>
<td>2.27</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Sistan</td>
<td>2.5%</td>
<td>0.53</td>
<td>161%</td>
<td>1.39</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Fars</td>
<td>2.5%</td>
<td>0.83</td>
<td>32%</td>
<td>1.10</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Gazvin</td>
<td>6.1%</td>
<td>0.34</td>
<td>72%</td>
<td>0.59</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Ghom</td>
<td>2.1%</td>
<td>0.71</td>
<td>130%</td>
<td>1.64</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Golestan</td>
<td>8.6%</td>
<td>0.63</td>
<td>176%</td>
<td>1.75</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Gilan</td>
<td>3.7%</td>
<td>0.72</td>
<td>116%</td>
<td>1.57</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Lorestan</td>
<td>4.8%</td>
<td>0.41</td>
<td>90%</td>
<td>0.79</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Mazandaran</td>
<td>3.6%</td>
<td>0.81</td>
<td>270%</td>
<td>3.00</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Markazi</td>
<td>7.6%</td>
<td>0.77</td>
<td>27%</td>
<td>0.98</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Hormozgan</td>
<td>2.5%</td>
<td>0.59</td>
<td>89%</td>
<td>1.11</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Hamadan</td>
<td>3.0%</td>
<td>0.53</td>
<td>170%</td>
<td>1.43</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Karaj</td>
<td>5.3%</td>
<td>0.59</td>
<td>182%</td>
<td>1.66</td>
<td>1,500</td>
<td>300</td>
</tr>
<tr>
<td>Kordestan</td>
<td>6.1%</td>
<td>0.91</td>
<td>153%</td>
<td>2.55</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>Kerman</td>
<td>5.4%</td>
<td>0.63</td>
<td>89%</td>
<td>1.18</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Kermanshah</td>
<td>1.2%</td>
<td>0.67</td>
<td>58%</td>
<td>1.06</td>
<td>750</td>
<td>150</td>
</tr>
<tr>
<td>Kohkiloye</td>
<td>4.9%</td>
<td>0.61</td>
<td>102%</td>
<td>1.22</td>
<td>350</td>
<td>70</td>
</tr>
<tr>
<td>Yazd</td>
<td>4.3%</td>
<td>0.60</td>
<td>152%</td>
<td>1.50</td>
<td>500</td>
<td>100</td>
</tr>
</tbody>
</table>
4.4 Capital requirement Estimation

The banks and financial institutes’ reports on measuring and credit risk management have exceeded the individual observations and limited case transaction, and are increasingly step to the level of macro observation, or in other words measuring and risk management portfolio of facilities and transactions.

Although the portfolio’s forming parts are the individual transactions of the bank with the customer, putting all of them in a collective basket will create diversification which in most cases will enable the managers to control the risk in the best way possible. In order to have more benefit which is the result of diversification and verification in credit and facilities portfolio in a bank, the risk control managers should have a proper answer for questions such as: how much the amount of the risk portfolio would be or how much and what amount of loss should be expected, in a risk exposed capital?

The reasons for choosing such approach in the case of risk can be explained as follow:

- Some risks are not either transferred or covered.
- These risks have got a complicated structure, which cause the improbability of their transitions expenses.
- Some of these risks play an important role in achieving the goals in the business.
- Some of these risks will limit the moral hazards.

Because of the above mentioned reasons, it is necessary that the banks attract, control and manage these risks in their portfolio. In order to manage such risks the banks can use one of the ways of increasing the variety, insurance or keeping the capital.

In reserving the capital, we are mentioning this point that all the banks risks can not be managed trough variety of insurances.

Therefore, the banks will always confront the unavoidable risks; these kinds of risks can be covered through reserving the capital. It can be said that the most important role of the capital especially from
the risk management point of view is to cover the risk by replacing the capital in the time of loss. For this same reason, the capital is considered as a reserve for the losses arising from the risk.

In this part, the common methods of measuring credit portfolio will be presented in brief, and then we will discuss credit risk\textsuperscript{+} method as a proper one in measuring portfolio credit risk in Post Bank of Iran as a commercial bank and in the end we will calculate the Economic Capital for the Post Bank of Iran.

**4.4.1 The main models of portfolio credit risk management:**

In order to effectively control and manage portfolio credit risk, we should at first estimate the value at risk and the probability of default and as a result the amount of the capital reserve for covering the imposed credit risks. For the same reason, a variety of methods have been compiled for measuring the portfolio credit risk, which according to their financial structure and achievable data, could be used by financial institutes.

The compiling stages of models are as follow:

- Studying the common methods of measuring credit risk and its conformity measuring.
- The probable model making of portfolio risk.
- Measuring portfolio risk through using analytic methods and resemblance.
- Calculating the amount of the bank’s needed economic capital

In chapter three we discussed the common models of portfolio credit risk management in detail. Here, we will illustrate a brief review of mentioned models:

**I. Credit Metrics:**

The function of this model is on the basis of analyzing the change of credit grades. In other words, it focuses on the probability of
transferring from one grade to another in a definite period of time which is usually one year.

II. Credit Portfolio View:
In this model, the probability of default changes according to credit cycle, and a function of macro-economical variables such as the economic growth rate, business cycles, rate of currency, rate of profit and the government expenditures.

III. KMV Model:
In this model, in order to achieve the value of the asset and its fluctuations, we can use the structural relationship between the market’s value of the shares, and the market value of the company’s asset, and also the relationship between the fluctuations of the company’s asset, and their shares.

IV. Credit Risk:
This method concentrates on the default event. In other words, this model estimates the expected loss of the given facilities and the distribution of the mentioned probabilities of these losses by concentrating on calculating the required capital reserves for the financial institution to confront these losses, which are usually higher than a definite level.

It should be mentioned that the creditportfolioview, and KMV models are based upon this experimental view that the default probability and the change of credit grade, will change during the time. The KMV model usually uses a macro economic view point, which relates the probability of default of each indebted to the market value of his assets. In the creditportfolioview, the macro economic factors are related to the changing of grade and default of each debtor.
CreditMetrics model is on the basis of credit grade change analysis. In other words, it focuses on the probability of transferring from one credit grade to the other, in a definite period of time.

CreditRisk+, by using the output (default probability) used by the banks to calculate the risk, can estimate the expectable loss of granting facilities and the distribution of probabilities of these losses on needed capital reserves of the financial institute to confront them.

Therefore, by considering the study of limitations and abilities of the mentioned models, it seems that from the viewpoint of calculating methods and needed data, Credit Risk+ is the best model for calculating portfolio credit risk and required capital.

This model in comparison with other models is more advanced from the statistical viewpoint, and also benefits from more adjustment of relationship through using the customers’ scoring model output.

Credit Risk+ model has the ability of determining the economic capital, which is needed for covering unexpected losses.

4.4.2 Estimation of Credit Risk+ model

In this part, an analytic technique is presented in order to establish a complete distribution of portfolio losses, which consists of value at risk. This technique can be used for each and every kind of portfolio in which the default rate of customers is small. In addition, by using such technique we can also establish a one year or multi-year loss distribution.

Through noticing the output data (probability of default) from logit model especially for Post Bank of Iran’s Credit customers, which are coincided with the conditions of Credit Risk+ model, we can use this model for estimating economic capital and also portfolio management. Therefore; at first we are going to study the data structure.
I. Statistical data:

The used data consists of all the P.B.I’s granted facilities, which at the time of this study are more than 66,573 cases. These facilities and credits have been given through different branches, and based on the branch’s authority have different amount and sizes. Used data have been mentioned in table (4.7).

As it is shown in the mentioned table, because of the large number of loan receivers, and also the characteristics related to each of the branches conditions, the facilities granted have been categorized to 35 groups. This will cause the shares and the effects of each of the branches on the bank’s credit portfolio. The average amount of default rate and also its standard deviation have been calculated from logit model for each of the levels, and finally as a result from the total portfolio.
Table (4.7) Basic data to estimate economic capital for the Post Bank of Iran

<table>
<thead>
<tr>
<th>No</th>
<th>Credit Pillar</th>
<th>Exposure</th>
<th>Mean default rate</th>
<th>Default rate Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Board of Director</td>
<td>73.914</td>
<td>5.3%</td>
<td>2.6%</td>
</tr>
<tr>
<td>2</td>
<td>Supreme Credit Commission</td>
<td>32.997</td>
<td>34.0%</td>
<td>17.0%</td>
</tr>
<tr>
<td>3</td>
<td>Azar- shargi</td>
<td>50.919</td>
<td>2.7%</td>
<td>1.4%</td>
</tr>
<tr>
<td>4</td>
<td>Azar-gharbi</td>
<td>87.646</td>
<td>3.8%</td>
<td>1.9%</td>
</tr>
<tr>
<td>5</td>
<td>Ardebil</td>
<td>38.153</td>
<td>5.2%</td>
<td>2.6%</td>
</tr>
<tr>
<td>6</td>
<td>Esfahan</td>
<td>146.027</td>
<td>6.4%</td>
<td>3.2%</td>
</tr>
<tr>
<td>7</td>
<td>Ilam</td>
<td>34.543</td>
<td>5.3%</td>
<td>2.7%</td>
</tr>
<tr>
<td>8</td>
<td>Boushehr</td>
<td>28.511</td>
<td>10.2%</td>
<td>5.1%</td>
</tr>
<tr>
<td>9</td>
<td>Chahar mahal</td>
<td>34.869</td>
<td>3.2%</td>
<td>1.6%</td>
</tr>
<tr>
<td>10</td>
<td>Khorasan jonobi</td>
<td>26.298</td>
<td>1.6%</td>
<td>0.8%</td>
</tr>
<tr>
<td>11</td>
<td>Khorasan razavi</td>
<td>98.439</td>
<td>4.4%</td>
<td>2.2%</td>
</tr>
<tr>
<td>12</td>
<td>Khorasan shomali</td>
<td>23.650</td>
<td>2.5%</td>
<td>1.3%</td>
</tr>
<tr>
<td>13</td>
<td>Khozestan</td>
<td>103.998</td>
<td>8.7%</td>
<td>4.3%</td>
</tr>
<tr>
<td>14</td>
<td>Zanjan</td>
<td>35.001</td>
<td>0.5%</td>
<td>0.3%</td>
</tr>
<tr>
<td>15</td>
<td>Tehran- South</td>
<td>128.145</td>
<td>2.7%</td>
<td>1.3%</td>
</tr>
<tr>
<td>16</td>
<td>Tehran- North</td>
<td>321.010</td>
<td>2.0%</td>
<td>1.0%</td>
</tr>
<tr>
<td>17</td>
<td>Tehran- Center</td>
<td>329.957</td>
<td>2.5%</td>
<td>1.2%</td>
</tr>
<tr>
<td>18</td>
<td>Semnan</td>
<td>22.177</td>
<td>2.5%</td>
<td>1.3%</td>
</tr>
<tr>
<td>19</td>
<td>Sistan</td>
<td>44.664</td>
<td>6.1%</td>
<td>3.0%</td>
</tr>
<tr>
<td>20</td>
<td>Fars</td>
<td>219.100</td>
<td>2.1%</td>
<td>1.1%</td>
</tr>
<tr>
<td>21</td>
<td>Gazvin</td>
<td>44.700</td>
<td>8.6%</td>
<td>4.3%</td>
</tr>
<tr>
<td>22</td>
<td>Ghom</td>
<td>38.163</td>
<td>3.7%</td>
<td>1.9%</td>
</tr>
<tr>
<td>23</td>
<td>Golestan</td>
<td>33.072</td>
<td>4.8%</td>
<td>2.4%</td>
</tr>
<tr>
<td>24</td>
<td>Gilan</td>
<td>140.197</td>
<td>3.6%</td>
<td>1.8%</td>
</tr>
<tr>
<td>25</td>
<td>Lorestan</td>
<td>47.777</td>
<td>7.6%</td>
<td>3.8%</td>
</tr>
<tr>
<td>26</td>
<td>Mazandaran</td>
<td>63.348</td>
<td>2.5%</td>
<td>1.2%</td>
</tr>
<tr>
<td>27</td>
<td>Markazi</td>
<td>53.426</td>
<td>3.0%</td>
<td>1.5%</td>
</tr>
<tr>
<td>28</td>
<td>Hormozgan</td>
<td>37.016</td>
<td>5.3%</td>
<td>2.7%</td>
</tr>
<tr>
<td>29</td>
<td>Hamadan</td>
<td>89.965</td>
<td>6.1%</td>
<td>3.1%</td>
</tr>
<tr>
<td>30</td>
<td>Karaj</td>
<td>88.555</td>
<td>5.4%</td>
<td>2.7%</td>
</tr>
<tr>
<td>31</td>
<td>Kordestan</td>
<td>37.592</td>
<td>1.2%</td>
<td>0.6%</td>
</tr>
<tr>
<td>32</td>
<td>Kerman</td>
<td>127.860</td>
<td>4.9%</td>
<td>2.4%</td>
</tr>
<tr>
<td>33</td>
<td>Kermanshah</td>
<td>63.713</td>
<td>4.3%</td>
<td>2.1%</td>
</tr>
<tr>
<td>34</td>
<td>Kohkiloye</td>
<td>27.961</td>
<td>5.1%</td>
<td>2.6%</td>
</tr>
<tr>
<td>35</td>
<td>Yazd</td>
<td>56.765</td>
<td>5.3%</td>
<td>2.6%</td>
</tr>
</tbody>
</table>
II. Running the model:

First output of the Credit Risk model is shown in table (4.8), containing Expected loss and Risk Contribution of the P.B.I’s’ Credit pillars.

<table>
<thead>
<tr>
<th>No.</th>
<th>Credit Pillar</th>
<th>Expected Loss</th>
<th>Risk Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Board of Director</td>
<td>3.914</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>Supreme Credit Commission</td>
<td>11.219</td>
<td>32</td>
</tr>
<tr>
<td>3</td>
<td>Azar- shargi</td>
<td>1.397</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>Azar-gharbi</td>
<td>3.296</td>
<td>13</td>
</tr>
<tr>
<td>5</td>
<td>Ardebil</td>
<td>1.975</td>
<td>6</td>
</tr>
<tr>
<td>6</td>
<td>Esfahan</td>
<td>9.324</td>
<td>52</td>
</tr>
<tr>
<td>7</td>
<td>Ilam</td>
<td>1.843</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>Boushehr</td>
<td>2.902</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>Chahar mahal</td>
<td>1.120</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>Khorasan jonobi</td>
<td>0.421</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>Khorasan razavi</td>
<td>4.366</td>
<td>19</td>
</tr>
<tr>
<td>12</td>
<td>Khorasan shomali</td>
<td>0.593</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>Khozestan</td>
<td>9.046</td>
<td>40</td>
</tr>
<tr>
<td>14</td>
<td>Zanjan</td>
<td>0.188</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>Tehran- South</td>
<td>3.437</td>
<td>18</td>
</tr>
<tr>
<td>16</td>
<td>Tehran- North</td>
<td>6.297</td>
<td>63</td>
</tr>
<tr>
<td>17</td>
<td>Tehran- Center</td>
<td>8.123</td>
<td>83</td>
</tr>
<tr>
<td>18</td>
<td>Semnan</td>
<td>0.558</td>
<td>1</td>
</tr>
<tr>
<td>19</td>
<td>Sistan</td>
<td>2.708</td>
<td>8</td>
</tr>
<tr>
<td>20</td>
<td>Fars</td>
<td>4.704</td>
<td>34</td>
</tr>
<tr>
<td>21</td>
<td>Gazvin</td>
<td>3.826</td>
<td>12</td>
</tr>
<tr>
<td>22</td>
<td>Ghom</td>
<td>1.424</td>
<td>4</td>
</tr>
<tr>
<td>23</td>
<td>Golestan</td>
<td>1.581</td>
<td>4</td>
</tr>
<tr>
<td>24</td>
<td>Gilan</td>
<td>5.023</td>
<td>28</td>
</tr>
<tr>
<td>25</td>
<td>Lorestan</td>
<td>3.644</td>
<td>11</td>
</tr>
<tr>
<td>26</td>
<td>Mazandaran</td>
<td>1.566</td>
<td>5</td>
</tr>
<tr>
<td>27</td>
<td>Markazi</td>
<td>1.580</td>
<td>5</td>
</tr>
<tr>
<td>28</td>
<td>Hormozgan</td>
<td>1.975</td>
<td>6</td>
</tr>
<tr>
<td>29</td>
<td>Hamadan</td>
<td>5.519</td>
<td>23</td>
</tr>
<tr>
<td>30</td>
<td>Karaj</td>
<td>4.747</td>
<td>20</td>
</tr>
<tr>
<td>31</td>
<td>Kordestan</td>
<td>0.433</td>
<td>1</td>
</tr>
<tr>
<td>32</td>
<td>Kerman</td>
<td>6.225</td>
<td>31</td>
</tr>
<tr>
<td>33</td>
<td>Kermanshah</td>
<td>2.737</td>
<td>9</td>
</tr>
<tr>
<td>34</td>
<td>Kohkiloye</td>
<td>1.426</td>
<td>4</td>
</tr>
<tr>
<td>35</td>
<td>Yazd</td>
<td>2.980</td>
<td>10</td>
</tr>
</tbody>
</table>
In the second column of the above mentioned table, the amount of the expected losses has been calculated by considering the value at risk, also the average of the default rate and related standard deviation.

Calculated risk contribution (third column, table 4.8) by the model, shows the final effect of each of the pillars on the chosen centile (here it is 99%) on the total loss of bank. The amount of shares will change according to the numerous and different centile. Through noticing the shares of different credit pillars from the portfolio risk of P.B.I, we will see that “Tehran-center”, “Tehran-north”, and “Isfahan” credit pillars have the most share of risk, which with a better credit risk management; they will have a more positive effect than other pillars of the bank. In other words, concentrating on these credit pillars will improve the bank’s credit portfolio.

Table (4.9) is related to the loss contribution which consists of the amount of loss, probability of loss and also cumulative amount of loss probability. The amounts of this table, are the basis for the calculations of economic capital, and also calculating the amount of losses in different percentiles.
Table (4.9): Loss contribution and related probability in Post Bank of Iran

<table>
<thead>
<tr>
<th>Credit Loss Amount</th>
<th>Probability</th>
<th>cumulative</th>
<th>Probability</th>
<th>cumulative</th>
<th>Probability</th>
<th>cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>23.49%</td>
<td>23.49%</td>
<td>204</td>
<td>0.57%</td>
<td>79.87%</td>
<td>95.62%</td>
</tr>
<tr>
<td>4</td>
<td>0.00%</td>
<td>23.49%</td>
<td>208</td>
<td>0.49%</td>
<td>80.37%</td>
<td>95.73%</td>
</tr>
<tr>
<td>8</td>
<td>0.00%</td>
<td>23.49%</td>
<td>212</td>
<td>0.49%</td>
<td>80.86%</td>
<td>95.89%</td>
</tr>
<tr>
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</tbody>
</table>
Here, table (4.9) is mostly used for estimating annual Credit provision (ACP). The expected loss of credit portfolio is equal to 122 billion rials. And in the chosen 99% percentile, credit portfolio loss (the Incremental Credit Reserve) is equal to 581 Billion Rials. Therefore the extra capital requirements for covering all the losses in the level of 99% under the Credit Risk+ model is equal to (581-122) =459 Billion rials. This amount of capital is known as Economic Capital. It should be noticed that all the value at risk by considering table (4.7) will rise above 2830 billion rials.
Table (4.10) is summarized format of table (4.9), which has illustrated amounts of credit loss by considering different levels of percentile.

Table (4.10): Credit Loss distribution in different percentiles

<table>
<thead>
<tr>
<th>Percentile</th>
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</table>

On the basis of tables (4.9) and (4.10) the figures (4.8) and (4.9) have been drawn.

Figure (4.8): Capital requirements for covering Expected loss and Economic capital in Post Bank of Iran

In figure (4.8) expected loss, unexpected loss (the amount of loss on the level of 99%) and economic capital, have been shown.
In figure (4.9) the vertical axis shows the cumulative probability up to 100%, and the horizontal axis represents the amount of losses related to various levels of cumulative probability.