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Measuring the Credit Risk of Bank Based on Z-Score and KMV-Merton Models: Evidence from Iran

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ABSTRACT

This paper examines the credit risk in the Iranian banks during 2008 to 2018 through the Z-score (Accounting based data) and the KMV-Merton (Market based information) models. In the Merton model, equity is equal to call option on underlying value of the bank's asset. The market value of assets is estimated by share price. The value of assets is then compared to the value of liabilities. Therefore, default when occurs that the market value of assets is less than the book value of debts. so, value of equity becomes negative. In the Z-score model, return on Assets and Equity to Assets as the numerator and standard deviation of ROA as the denominator are applied. If the mentioned ratios of numerator increase and the denominator decrease, the probability of default decline. As well as, Independent variables are divided into five groups: leverage, management efficiency, profitability quality, financial health, and liquidity. As a result, capital adequacy and profitability have a greater impact on both models. Also, the ANOVA table proves the validity of two models. The value of ROC test in both models is above average (0.5) which are efficient and their efficiency is 99.48% and 92.68%, respectively. Also, in terms of Voung's test, the KMV is more efficient than the Z-score.

1 Introduction

The main activity of bank is developing credit to borrowers by paying loans. Also, an important section of bank's risk relates to the quality of its assets that should be in line with that bank's risk appetite. Credit risk is perceived as the most important risk in the financial system. In order

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to manage credit risk efficiently, quantifying risk with the most advanced statistical tools is essential. In the process of identifying the customer's credit risk, aim is to determine a measure to examine the customer's inability to meet obligations to the bank, while in evaluating the bank’s credit risk, purpose is to identify the bank's ability to repay its obligations to depositors and other creditors. For evaluation bank’s credit risk, in addition to examining the quality of assets, the items such as debt maturity, equity, profitability and the relationship between assets and liabilities should be examined. Also, the customer's credit risk has a direct effect on the bank's credit risk, and with increasing the probability of customer default, the bank's credit risk will be increased. So, if the bank has a high level of Net Performing Loans (NPL), the net cash flow decreases and the bank can’t pay its debts on time, then insolvency risk and bankruptcy risk in bank will rise. According to research of Abinzano et al [1] the most classic models are based on accounting information. Models such as Altman’s [2] Z-score or Ohlson’s [3] O-score are based on financing data. Another alternative is the group of measures based on the price of equity of a company, such as Moody’s KMV model. In studying the relationship between credit risk and the momentum effect, several authors use different measures for proxying credit risk, and obtain different results. In this regard, Avramo et al [4] used the credit rating model, Abinzano et al [5] used the Black and Scholes model, and Agarwal and Toffler [6] apply the Altman Z-score model and show the results as a binary variable to differentiate between healthy and distressed companies. According to survey of Niklis et al [7] an important issue in credit risk is the correct estimation of the probability of default (PD). Credit rating models (CRM) are mainly used for this purpose and classify clients into different risk groups. In this method, financial information is combined with non-financial data into an aggregate index indicating the credit risk of the firms and can be constructed with a variety of statistical, data mining, and operations research techniques (e.g., logistic regression, neural networks, support vector machines, rule induction algorithms, multicriteria decision making, etc.). Comprehensive reviews in this area have been done by Thomas [8], Paoageorgiou et al. [9], and Abdou and Pointon [10]. Despite their success and popularity, credit scoring models are often static and based on historical accounting data that describes a company's past and may not be able to predict adequately the company's future and the trends in the business environment [11].

The weaknesses of accounting-based credit scoring models have led to the development of other alternative methods, among which structural models have become more popular. Structural models are based on the Black Scholes and the contingent claims approach and use market information to measure the probability of default. In efficient markets, all information related to the current situation of the company and the expectations of future developments of the company is reflected in stock prices. [11]. In addition, market data is constantly updated and investors consider updated information related to a company's performance. These features of market data reflect their better performance in predicting default and measuring credit risk. The results of studies by Hillegeist [12] and Agarwal and Toffler [11] show that market models perform better than accounting-based models. According to Li and Miu [13] and Yeh et al. [14], market models have also been shown to contribute in the construction of improved hybrid systems in combination with accounting-based models. Despite good predictive power and a strong theoretical foundation, market models are limited to listed companies. According to Syversten [15], Moody's KMV RiskCale^{TM} model, which has been used in different countries with positive results, has a commercial application. Altman et al. [2] used data from US companies to investigate the potential development of multivariate regression models that estimate the probability of default in market models. They concluded that both methods should be used as complementary source of information. With the aim to quantifying credit risk of bank, this paper has two focuses. First, the efficiency of both models based on accounting data and market information is measured, and second, which model is more efficient.

2 Literature Review

There are a number of researches conducted by authors about comparing financial models based on historical data against to structural models relying on share price. In the following paragraphs, we explain them. Credit risk in conventional banks was compared with Islamic banks by using the Merton model, and with measure of the Distance-to-Default (DD) and Default Probability (DP) from 2005 to 2009. Islamic banks due to having a higher maturity average have more credit risk than conventional banks. The average of distance to default in Islamic banks is 204 and in conventional banks is 15. However, the probability of default in Islamic and conventional banks is 3.5% and 5.7%, respectively, which indicates that credit risk is high in both banking groups. [16]. The Black and Schulz –Merton model with accounting ratios model was compared by using data from listed and non-listed companies during the period 2005-2010 in Greece. Financial ratios include of profitability ratios (gross profit to sales and return on assets), debt ratios (total liabilities to total assets and interest expenses to sales), liquidity ratios (current assets to short term liabilities and sales to short term liabilities) Management efficiency (accounts receivable turnover). They combine market-based and accounting-based models for credit rating. The result is that the Merton-Black and Schulz model is more efficient than traditional credit rating models that use historical default data. Although the Merton model measurement was based on market and stock price information and was used for listed companies, this model could be used to measure the credit risk of non-listed companies by using financial data. [7]

The performance of credit risk models including market data-based models and accounting data-based models were examined to predict the inability of companies to meet their obligations. As a result, market-based models performed better than accounting-based models. A number models including cash flow ratio to total debt, size and ratio of book value to market value and multivariate models including Z-Altman model, Z-Toffler model, logit model, artificial network model, Merton model and etc. were tested. As a result, the performance of the models was generally lower than that mentioned in the literature. The performance of accounting information-based models was worse than market-based information models. [17]. The risk of the bank's inability to fulfillment of obligations through Z-score model in Islamic banks by using 553 samples from 24 countries from 1999 to 2009 was examined. As a result, small Islamic banks have a lower credit risk than conventional banks. So small Islamic banks are more stable in terms of insolvency risk. [18]. The Z-score model as a financial stability index was used to measure the insolvency risk. The credit risk of conventional banks and Islamic banks was examined by using data from 16 Asian countries between 2000 and 2008. As a result, the Z-score model in large Islamic banks is higher than conventional banks, which shows that the risk of insolvency in large Islamic banks is lower compared to conventional banks. [19]. The credit risk in Islamic banks and conventional banks from 13 countries and from 156 conventional banks and 37 Islamic banks between 2000 and 2012 was examined. Model based on accounting information including Z-score model, NPL ratio and loan loss reserve ratio, and model based on market information including Merton model and Distance of Default (DD) were used. The results show that, Islamic banks have significantly lower credit risk than conventional banks when it is measured by DD and NPL ratio. In contrast, Islamic banks have higher credit risk when it is measured by Z-score. [20]. In a survey, the credit risk management and performance of banks in Ghana by using the CAMELS rating model for 10 banks over a 7-year period Examined. The finding indicated that Earning has as highly considerable factor that affects the performance of banks. A percentage change in earning will result in 82.5% rise in bank performance which this measured by ROE. Capital adequacy, Management efficiency, Asset quality, and Liquidity were equally affecting on the performance of banks. Sensitivity is insignificant factor of the CAMELS model that affects the performance of the banks in Ghana. [21]. Another author [22] used models based on the bank's internal ranking and based on a sample of data from different countries, concluded that if the bank uses this model to measure credit risk, profit will eventually increase. The net interest margin (NIM) is fundamental for bank profitability and solvency. In addition, IRB models improve credit risk-management, and this improvement is accompanied by lower funding costs and higher investment in interest earning assets. The use of internal rating models by banks after the financial crisis of 2008-9 has been considered by regulators and its use has improved profitability, increased dividends to shareholders and strengthen the liquidity of banks.

In a survey [23], the impact of prudential regulations examined on the failures risk of bank in the Eurozone during the financial crisis. The Z-score and the rating are two indicators of bankruptcy risk measures. CAMEL variables, regulatory variables, and macroeconomic-level variables were used. The results show that, regardless of the method applied to measure the risk of bankruptcy, variables such as the improving of equity, the level of liquidity, and supervision of banking activities are important. In addition, the Z-score, as a method of assessing the banking risk, shows a better performance compared to the rating.

3 Methodology

The method of calculating the dependent variable is examined through two models of Z-Score and KMV-Merton. Independent variables include fifty variables, four of which are auxiliary. Independent variables are divided into five groups: leverage, management efficiency, profitability quality, financial health and stability, and liquidity. The description of independent variables and their sources are showed in Appendix of A1. Then we run models by Pearson’s regression. Therefore, to test statistical hypotheses, regression analysis, analysis of variance, Roc and Voung’s test were used. Excel software is used to process the collected information and specialized software (SPSS) is used for statistical analysis of the processed data. Due to the fact that a lot of data is processed in Excel and it is possible to transfer information from Excel to SPSS software, this software has been used. Also, correlation coefficient, determination coefficient, standard error of the estimate, Durbin-Watson statistic, Roc statistic and analysis of variance (ANOVA) table can be extracted in the output of SPSS software.

3.1 Model of Z-Score (Financial Stability Index)

According to the research of IMF [24], the following Z-score index was used as an indicator of financial stability to cover the credit risk. We run this model as one the dependent variables.

$$Z-score_{s,j,t}=\left(ROA_{s,j,t}+\frac{E_{s,j,t}}{A_{s,j,t}}\right)S.D(ROA)$$

ROA = Return on Assets, which is obtained by dividing the net profit by the total assets.

E / A = Total Equity divided by Total Assets

S.D (ROA) = the standard deviation of the return on assets over the past three years.

The Z-score index follows the normal distribution function, so the confidence interval is as follows:

$$\hat{\mu} - z_{\alpha/2}.\sigma_x \leq \mu \leq \hat{\mu} + z_{\alpha/2}.\sigma_x$$

$$\mu \pm \varepsilon \;;\; \varepsilon = z_{\alpha/2}.\sigma_x \;;\; \varepsilon = Z_{score}.\sigma_{ROA}$$

$$z_{\alpha/2} = \frac{\mu}{\sigma_x} \;;\mu = ROA\,;\sigma_X = \sigma_{ROA}$$

If the following condition happens, default will occur:

$$P_r(\mu \leq E) \rightarrow p_r\left(\mu \leq \frac{Equity}{Asset \times Z_{score}}\right)$$

However, if the value of assets is less than the value of its debts, the probability of default is determined by the following equation.

$$p(\mu \leq E) = \int_{-\infty}^{k} \emptyset(\mu) d\mu$$

Therefore, it is possible to accurately assess the inability to fulfill the obligations through the following criteria.

$$p_r(r_i \leq -e_i) = p_r\left(\frac{r_i - \mu_r}{\sigma_r} \leq z\right) = \varphi r_i(-Z)$$

The linear relationship of Pearson's regression to test the first hypothesis is as follows:

$$Z - score_{s,j,t} = \left(ROA_{s,j,t} + \frac{E_{s,j,t}}{A_{s,j,t}}\right) S.D(ROA) = \beta_0 + \beta_1 x_1 + \cdots + \beta_{50} x_{50\varepsilon}$$

3.2 Merton-KMV Model

This model has been used by some researchers [7], [11] and [25]. According to Merton model, the total market value of the company's assets is assumed to be

$$dV_A = \mu V_A dt + \sigma V_A dW \tag{1}$$

In this model V_A is equal to the value of the company's assets. σ_A is equal to the standard deviation of the rate of return on assets or asset volatility and dW is a standard Weiner process. μ is equal to the expected rate of return on assets. It is also assumed that the company issues bonds with discount with maturity in T-periods. Under this assumption, equity is equal to call option on underlying value of the firm's asset with a strike price, denoted by V_A, equal to the face value of firm's debt, X and a time to maturity of T. Therefore, default when occurs that the market value of assets is less than the book value of debts, in which case the value of equity becomes negative. According to this model, the current value of equity (V_E) can be expressed by the pricing formula of Black and Schulz.

$$V_E = V_A N(d_1) + X.e^{-rT} N(d_2) \tag{2}$$

$$d_2 = d_1 - \sigma_A\sqrt{T}$$

$$d_1 = \frac{ln\left(\frac{V_A}{X}\right) + (r + 0.5\,\sigma_A{}^2)T}{\sigma_A\sqrt{T}} \quad (3)$$

r is equal to the risk-free interest rate. σ_A is the standard deviation of the rate of return on asset and N is the function of cumulative normal distribution. The researchers tried to make the model operational by changing some of the assumptions mentioned. In this regard, Niklis et al. using a model based on Merton model (KMV) as follows to measure the probability of default.

$$\sigma_E = \left(\frac{V_A}{E}\right) + \frac{\partial E}{\partial V}\sigma_A \quad (4)$$

In the Black-Scholes-Merton model, $\frac{\partial E}{\partial V} = N(d_1)$so, the company's volatility and equity are equal to

$$\sigma_E = \left(\frac{V_A}{E}\right) + N(d_1)\sigma_A \quad (5)$$

Therefore, the distance to default (DD) and probability of default (PD) can be calculated as follows.

$$PD_{sjt} = N(-DD_{jt})\ ,\ DD_{jt} = \frac{ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - 1/2\,\sigma_A{}^2\right)T}{\sigma_A\sqrt{T}} \quad (6)$$

$V_A$is equal to the value of the assets, σ_A is the volatility of the assets, X_t is the total liabilities, μ is the expected return on the assets, T is the time period and N is the cumulative probability distribution. The Distance to Default is defined by the number of standard deviations of market value of firms away from the default point. [26] The higher distance to default indicates that the value of the assets is far from the default point and therefore reduces the probability of default. In order to solve Equation 6, Equations 2 and 5 need to be solved simultaneously. In the KMV model, these equations cannot be solved numerically and simply. Therefore, this problem can be solved by implementing the following equation. First, for the initial value of the company, it is assumed that $\sigma_v = \sigma_E[E/(E+F)]$ and the market value of the debt of each bank are the same as the nominal value of its debt. Since banks that are more prone to bankruptcy have higher debt risk and their debt risk is correlated with the value of their equity value, the standard deviation of the company's debt is calculated as $\sigma_D = 0.05 + 0.25 * \sigma_E$. In this equivalent, 5% is added to show the standard deviation of the structure. Also, 25% multiplied by the standard deviation of equity is added to calculate the standard deviation of the whole company.

$$\sigma_v = \frac{E}{E+D}\sigma_E + \frac{D}{E+D}(0.05 + 0.25 * \sigma_E)$$

Then the expected rate of return on the value of the company's assets is equal to the rate of return on the company's assets in the past year or $\mu = r_{it-1}$ therefore, using μ estimates according to past returns, the distance to the default is equal to

$DD_{jt} = \frac{ln(E+F/F) + \left(r_{it-1} - 0.5 * \sigma_V^2\right)T}{\sigma_V\sqrt{T}}$ And Probability of default is $PD_{jt} = (-DD)$

The linear relationship of Pearson's regression to test the second hypothesis is as follows:

$$PD_{jt} = (-DD) = \beta_0 + \beta_1 x_1 + \cdots + \beta_{50} x_{50+\varepsilon}$$

3.3 Sample and Data

In this study, 18 samples from 31 Iranian banks have been selected due to the sample activity should be at least 7 years. Some data of models includes of independent and dependent variables are extracted from audited financial statements at the end of the financial year. For example, all revenue and profit items are deducted from the financial statements because the revenue recognized must be real and certified by an independent auditor. But some accounting items have been adapted from the general ledger due to quarterly review. For example, quarterly changes in assets and liabilities listed in general ledger have a more realistic impact on model data than on financial statements. In order to implement the KMV-Merton model, it is necessary to determine the price of per share. Therefore, banks with at least 7 years of experience are mentioned in the sample. Also, some banks, which have been operating for more than 7 years but are not active in the stock exchange market due to their state ownership, the market price of each bank share is determined by the industry-related P/E estimation multiplied by the estimated price of per share. Therefore, the sample includes all state-owned banks as well as some member banks of the Securities and Exchange Organization that have been established for at least 7 years.

3.4 Statistical Tests

Hypothesis 1 - Credit risk forecasting of the bank based on Z score model is efficiency
To test the above hypothesis, following statistics were extracted.

Table 1: Some Pearson’s Regression Statistics Regarding Z-Score Model

Model	R	R Square	Adjusted R Square	Std Error of the Estimate	Durbin-Watson
Z score	0.848	0.719	0.699	0.81644	1.074

According to the table, the adjusted coefficient of determination shows that 69.9% of the changes in the model are influenced by the independent and real control variables that are included in the model. Durbin-Watson statistic is 1.074, which indicates a low periodic correlation between residual errors. Given that in this model there is a correlation between residuals of the model and considering that part of the correlation coefficient and the coefficient of determination may be false due to linear correlation between variables, Roc statistic is used to measure the efficiency of the model.

Table 2: ANOVA - Z-Score Model

Model	Sum of Square	df	Mean Square	F	Sig
Regression	11.739	48	0.245	36.688	0.000
Residual	4.593	689	0.007		
Total	16.332	737			

According to the table above, the Z-Score model is valid and there is a linear relationship between the predictor variables (independent) and the dependent variable. Since the level of significance or the value of computational statistical probability relate to F is less than the level of error of 5%, so the model has the necessary validity and the coefficients of the independent variables are significantly different from zero.

$$\begin{cases} H_0 = \beta_1 = \beta_2 = \ldots = \beta_{50} \\ H_1 = \text{At least one of } \beta_j \text{ is opposite zero} \end{cases}$$

The result H_1 is accepted because one of the betas is against zero. In other words, since the significance coefficient is less than 5% beta, H_0 so is rejected.

Table 3-Area Under the ROC Curve - Z-Score Model

Sample	Area	Std.Error	Asymptotic 95% Confidence Interval	
738	0.9268	0.0096	0.90791	0.9456

The value of ROC (Z) test statistic is equal to 92.68. To test the above hypothesis, since the absolute value of the score (Z) is computationally greater than its critical value in the 95% confidence interval $(Z_{OBSt} \succ 1/96)$, the hypothesis H_0 is rejected and the hypothesis H_1 is accepted. Therefore, the model has the necessary validity and the coefficients of the independent variables are significantly different from zero

$$\begin{cases} H_0 = ACU_{Z-score} = ACU_{KMV} \\ H_1 = ACU_{Z-score} \neq ACU_{KMV} \end{cases}$$

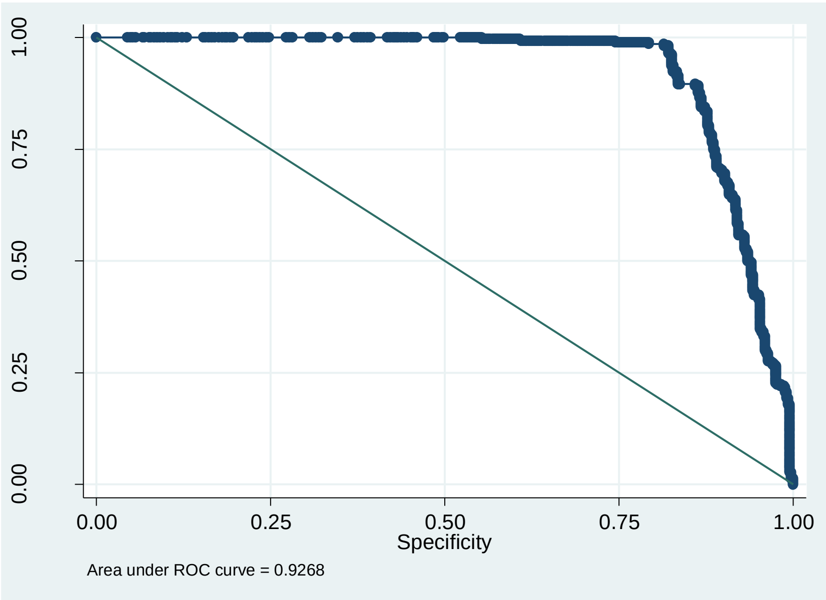

Fig.1: ROC Curve - Z-Score model

Hypothesis 2 -Credit risk forecasting of the bank based on KMV-Merton model is efficiency

To test the above hypothesis, following statistics were extracted.

Table 4: Area Under the ROC Curve - KMV-Merton Model

Model	R	R Square	Adjusted R Square	Std Error of the Estimate	Durbin-Watson
KMV	0.795	0.631	0.606	0.13076	0.723

According to the table, the adjusted coefficient of determination in Merton model is equal to 60.6%, which shows that 60.6% of the changes in Merton model are affected by independent and real control variables that are entered in the model. The standard error of the Estimate in the Merton model is 0.13076, which is relatively low. In this model, the value of Durbin-Watson is equal to 0.723 which indicates the correlation between the residues of the model. Given that in this model there is a correlation between residuals of the model and considering that part of the correlation coefficient and the coefficient of determination may be false due to linear correlation between variables, Roc statistic is used to measure the efficiency of the model

Table 5: Area Under the ROC Curve - KMV-Merton Model

Sample	Area	Std.Error	Asymptotic 95% Confidence Interval	
738	0.9948	0.0020	0.99098	0.99863

The value of Rock (Z) test statistic is equal to 99/48 To test the above hypothesis, since the absolute value of the score (Z) is computationally greater than its critical value in the 95% confidence interval $(Z_{OBSt} \succ 1/96)$, the hypothesis H_0 is rejected and the hypothesis H_1 is accepted. Therefore, the model has the necessary validity and the coefficients of the independent variables are significantly different from zero

$$\begin{cases} H_0 = ACU_{Z-score} = ACU_{KMV} \\ H_1 = ACU_{Z-score} \neq ACU_{KMV} \end{cases}$$

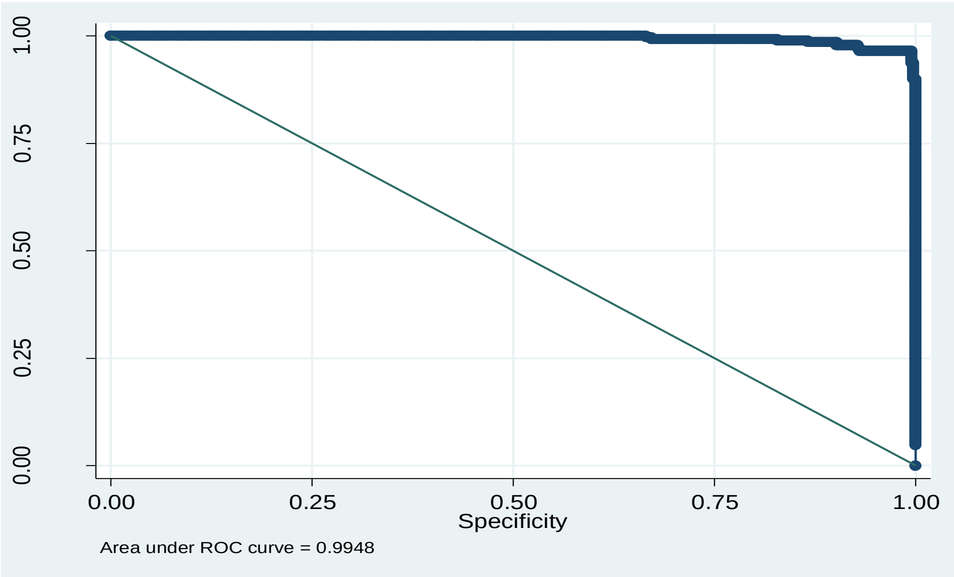

Fig.2: ROC Curve - KMV-Merton

Table 6: ANOVA - Z-Score Model

Model	Sum of Square	df	Mean Square	F	Sig
Regression	20.172	48	0.420	24.587	0.000
Residual	11.781	689	0.17		
Total	31.953	737			

According to the table above, the Z-Score model is valid and there is a linear relationship between the predictor variables (independent) and the dependent variable. Since the level of significance or the value of computational statistical probability relate to F is less than the level of error of 5%, so the model has the necessary validity and the coefficients of the independent variables are significantly different from zero.

$$\begin{cases} H_0 = \beta_1 = \beta_2 = \ldots = \beta_{50} \\ H_1 = \text{At least one of } \beta_j \text{ is opposite zero} \end{cases}$$

Hypothesis 3-Bank credit risk forecasting based on Z-Score Model is more efficient than KMV-Merton model

To test the above hypothesis, following statistics were extracted.

Table 7: Area Under the ROC Curve - Z-Scoreand KMV-Merton Model

Model	Sample	Area	Std.Error	Asymptotic 95% Confidence Interval	
Z-Score	738	0.9268	0.0096	0.90791	0.9456
KMV-Merton	738	0.9948	0.002	0.99098	0.99863

The area under the Roc curve is calculated to be 92.68% for Z-Score model and 99.48% for the Merton model, since these are not the same ($Z_{KMV} = \frac{0.9948}{0.002} = 497.4$, $Z_{FSI} = \frac{0.9268}{0.0096} = 96.54$), so the hypothesis that the area under the curve is equal in both models is rejected .The result is that the Merton model is more efficient in predicting the probability of default than the Z-Score model.

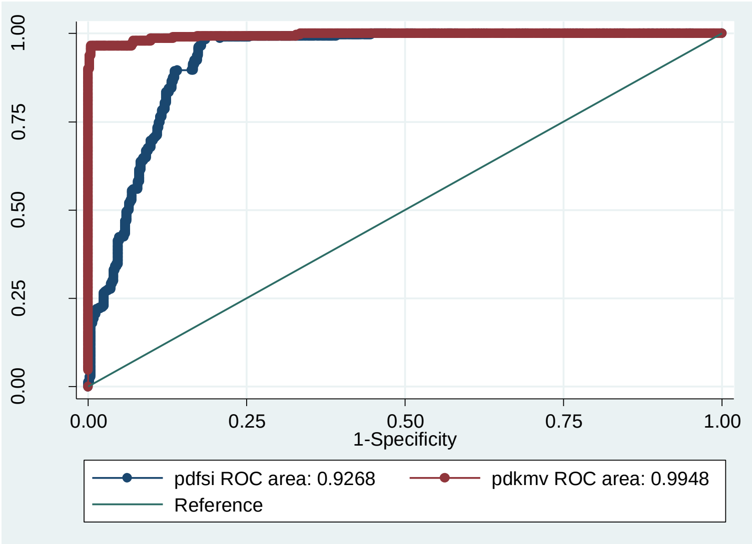

Fig.3: ROC Curve - KMV-Merton Versus Z-Score Model

Voung's test can also be used to examine and compare the two models. In this test, the coefficients of determination of the model are compared in pairs to determine whether there is a significant difference between the coefficients of determination of the two models or not. In Wong test, the null hypothesis is tested in comparison with the opposite hypothesis and at the error level (α). Therefore, if two hypothetical models with identifiers $M_2, M_1$are considered, the statistical hypothesis test is:

$$H_0 = \left(\frac{LR\ (M_1)}{LR\ (M_2)}\right) = 0$$

$$H_1 = \left(\frac{LR\ (M_1)}{LR\ (M_2)}\right) =< \text{or} > 0$$

The criterion for calculating the Z statistic of Voung's test is as follows"

$$Z=\frac{Ln\left(\frac{LR\;((M_1)}{LR\;((M_2)}\right)}{\sqrt{n}.\hat{w}^2}=\frac{1/2[Ln\left(\frac{\sigma^2 M_1}{LR\;(M_2)}\right)+\sum_{n=1}^{n}(\frac{e^2 M_{1i}}{2\sigma^2 M_1}-\frac{e^2 M_2}{2\sigma^2 M_2})}{\frac{\sqrt{n}}{n}-\sum_{i=1}^{n}[1/2Ln\left(\frac{\sigma^2 M_1}{2\sigma^2 M_2}\right)+(\frac{e^2 M_{1i}}{2\sigma^2 M_1}-\frac{e^2 M_{2i}}{2\sigma^2 M_2})-(1/2LR)^2}$$

$$\sigma_{M_1}^2=\frac{RSS_{M_1}}{n},\sigma_{M_2}^2=\frac{RSS_{M_1}}{n},e_{M_{1,i}}=f_1(x_1,x_2,\ldots,x_n)-\beta_0-\sum_{i=1}^{n}x_i\,,e_{M_{2i}}$$

The method of confirming or rejecting the hypothesis of H_1 is that if the statistical value (Z) of Voung's test is significant (α> p-value) and positive at the level of error (α), the pattern (M_2) will be superior to the pattern (M_1) and the standard error (SE) is less, but if the statistical value (Z) of Voung's test is not significant (α <p-value) at the error level (α), the pattern (M_1) is preferable to the pattern (M_2) and the standard error (SE) is less. The result of comparing the two models through Voung's statistic is as follows:

Table 8: Voung's Test of Z-Score (FSI) and KMV-Merton Model

Observations (Firms/Years)	738
Average (LR)	0.320916954
St.Deviation	0.740576359
zVOUNG'S Statistics	11.77202021
P-Value (SIG)	0.0000000
Model (FSI) Versus Model (KMV)	(1) vs. (2)

$$\text{Voung's test }=\left(\frac{\sqrt{\text{Observations}}*\text{Average (LR)}}{\text{St. Deviation}}\right)=11.77$$

$$\text{Voung's test }=\left(\frac{LR\;(M_1)}{LR\;(M_2)}\right)=11.77$$

Since Voung's test is greater than zero and equal to 11.77 percent and p-value is less than 5 percent, so the KMV model is preferable to the Z-Score model. In other words, the result of Voung's test shows that the KMV model is more efficient than the Z-Score model.

4 Conclusion

The objective of this paper is to investigate whether models based on finance data or market data are efficient, and which one of models is more efficient. Numerous studies have been conducted in this regard. So that, Kealhofer [27] compared the KMV model with the SandP rating model. Hellegeist [12] compared the Altman and Ohalsons Z models with the Merton-Beck and Schulz models. Gharghori [28] compared the Black and Scholes-Merton model with the Z-score accounting model, and Hilsher and Wilson [29] compared the credit rating model with the accounting information-based model. The results of all these researches show that market-based models have better performance in identifying the probability of default than accounting-based models. Market-based models use market data to assess the probability of default. In efficient markets, stock prices show all the information related to the current status of the companies as well as expectations relating their future developments. Also, market data are constantly updated as the investors consider update information relevant to the result of a firm. On the other hand, finance-based information models may not be valid due to accounting statements present past performance of a firm and may not be informative in predicting the future, the true asset values may be very different from the recorded book values, and accounting numbers are subject to manipulation by management. In this study, 18 samples were selected from 31 Iranian banks during 2008 to 2018. Also, credit risk assessment is performed by using an accounting-based model (retrospective) and a market-based model (prospective) to determine the performance of each.

As mentioned, Independent variables include fifty variables which four of them are Auxiliary. Based on A3 Appendix, the variables of X_1, X_8, X_{24}, X_{30}, X_{32}, X_{33}, X_{39}, X_{48}, and X_{49} have more influence on KMV-Merton Model. This means that the ratios such as ROA, ROE and items such as assets with favorable quality have greater effect on dependent variable. In addition, according to A4 Appendix, the variables of X_3, X_4, X_{14}, X_{15}, X_{31}, X_{36}, X_{38}, X_{40}, X_{41}, X_{43}, X_{44} and X_{45} have considerable effect on Z-score Model. These variables mainly include capital, profitability and non-performing loans (NPL). As a result, as the NPL level increases and the desired assets on the balance sheet decrease, the profitability diminishes. This situation leads to a decrease in capital adequacy and the probability of default ultimately increases. As well as, the correlation coefficient and adjusted coefficient of determination of both models are relatively high. Also, the result of analysis of variance of both models shows that the validity of the models is high and there is a linear relationship between the predictor (independent) variables and the dependent variable. Therefore, the both models are valid and the coefficients of the independent variables are significantly different from zero. According to the results of ROC and Voung's test, Merton's KMV model is more efficient and therefore can estimate bank's default accurately. This means that by estimating the market value of assets, the bank's ability to repay debts can be better assessed.

These positive preliminary results indicate that there is potential for future research that provide new insights into credit risk modeling. A first obvious direction would be to apply a set of predictors related to the non-financial sector of the firms, such as personnel, board member, corporate governance, and macroeconomic variables, such as inflation, GDP growth. It is also essential to examine the applicability of this modeling approach to economic growth. As noted, the market-based information model is more efficient in estimating default than the accounting-based model, which indicates a better and more accurate measurement of the bank's inability risk by estimating the day value of equity and the market value of the bank's assets. In this regard, in some countries, advanced mathematical and statistical models have been designed and used to accurately assess the credit risk of companies, the results of which can be seen in the very accurate ranking of companies by international rating companies such as Moody's, Fitch and S&P. It is therefore suggested that Future research is based on the latest models used by these companies.

5 Appendices

A1: Definition of the Variable and Data Source

Variables	group	Code	Description	Sources
x_1	Leverage	$SAEQ_{jts}$[a]	Sum assets to equity	[20]
x_2	Leverage	$SLRA_{jts}$	Sum liabilities to receivable assets	[7] [1]
x_3	Leverage	$NOPFC_{jts}$	Net operating profit to financing costs	CBI[b]
x_4	Leverage	$NPLSL_{jts}$	Non-Performing Loans (NPL[c]) to sum liabilities	[32]
x_5	Leverage	$ODLTD_{jts}$	Overdue loans to total deposits	[18]
x_6	Leverage	$PDTD_{jts}$	Past due loans to total deposits	[18]
x_7	Leverage	$DFLTD_{jts}$	Doubtful loans to total deposits	[18]
x_8	Leverage	$FASL_{jts}$	Fixed assets to sum liabilities	[32]

A1: Definition of the Variable and Data Source

Variables	group	Code	Description	Sources
x_9	Leverage	$SDTD_{jts}$	Sundry debtors to total deposits	CBI
x_{10}	Efficiency	$SGANPL_{jts}$	Seasonal growth average of NPL	[18]- [20]
x_{11}	Efficiency	$CRTR_{jts}$	Common revenue to total revenue	CBI
x_{12}	Efficiency	$NCRTR_{jts}$	Non-common revenue to total revenue	CBI
x_{13}	Efficiency	$PNPL_{jts}$	Provision of Non-performing loans (NPL)	[32] [18]
x_{14}	Efficiency	$CRSTRB_{jts}$	Common revenue of a sample to total revenue of banks	CBI
x_{15}	Efficiency	$OBTA_{jts}$	Off-balance sheet to total assets	CBI
x_{16}	Efficiency	$TFSSA_{jts}$	Total facilities and receivables to total assets	[24]
x_{17}	Efficiency	$LERC_{jts}$	Large exposure to regulatory capital	CBI
x_{18}	Efficiency	CBR_{jts}	Costs to revenue	[18]- [19]
x_{19}	Efficiency	$SDSA_{jts}$	Sundry debtors to sum assets	CBI
x_{20}	Liquidity	$NPLTF_{jts}$	NPL to total facilities	[18]- [33]
x_{21}	Liquidity	$ODLTF_{jts}$	Overdue loans to total facilities	[18]
x_{22}	Liquidity	$PDTF_{jts}$	Past due loans to total facilities	[18]
x_{23}	Liquidity	$DFLTF_{jts}$	Doubtful loans to total facilities	[18]
x_{24}	Liquidity	$CSST_{jts}$	Cash and Simi cash to short-term liabilities	[31]
x_{25}	Liquidity	$ACPRL_{jts}$	Average collection period of receivables/loans	CBI
x_{26}	Liquidity	$ARPLD_{jts}$	Average repayment period of long-term deposits	CBI
x_{27}	Liquidity	$SDTD_{jts}$	Short-term deposits to total deposits	[22]
x_{28}	Liquidity	$SLLL_{jts}$	Short-term loans to long-term loans	[32]
x_{29}	Liquidity	DC_{jts}	Deposit concentration ratio	CBI
x_{30}	Profitability	$ROPA_{jts}$	Return on operating assets	[18]
x_{31}	Profitability	ROA_{jts}	Return on assets	[30]- [20]
x_{32}	Profitability	ROE_{jts}	Return on equity	[18] [23]
x_{33}	Profitability	$CFOTQ_{jts}$	Cash result from operating activities to total equity	[33]
x_{34}	Profitability	$CFOTL_{jts}$	Cash result from operating activities to total facilities	[33]
x_{35}	Profitability	$CFOTR_{jts}$	Cash result from operating activities to total revenue	[33]
x_{36}	Profitability	$NPTR_{jts}$	Net profit to total revenue	[18]
x_{37}	Profitability	$NOPCF_{jts}$	Net operating profit to cash from operating activities	[32] [1]
x_{38}	Profitability	$NOPTRA_{jts}$	Net operating profit to total recoverable assets [b]	[20] [1]
x_{39}	stability	ADQ_{jts}	Accumulated dividends to equity	[1]
x_{40}	stability	CA_{jts}	Capital adequacy	[21] [23]
x_{41}	stability	$CCRWA_{jts}$	Core capital to risk-weighted assets	[21] [23]
x_{42}	stability	$PNPLPC_{jts}$	Provision of NPL to paid-up capital	[20]
x_{43}	stability	$T2RWA_{jts}$	Supplementary capital to risk-weighted assets	[21]
x_{44}	stability	$OBEQ_{jts}$	Off-balance sheet to equity	CBI
x_{45}	stability	$EQRA_{jts}$	Equity to receivable assets	[1] [23]
x_{46}	stability	$NOPRC_{jts}$	Net open position to regulatory capital	[21]
x_{47}	Auxiliary	AGE_{jts}	Life cycle of the bank [d]	[35] [36]
x_{48}	Auxiliary	SIZ_{jts}	Bank size [e]	[18]- [19]
x_{49}	Auxiliary	OWN_{jts}	Type of ownership [f]	CBI
x_{50}	Auxiliary	COM_{jts}	Competitiveness Index [g]	CBI

a: The index of j, t, s represents testable sample, time (year) and season respectively.
b: The Central Bank of Iran Regulations
c: It is the total assets of the bank after deducting NPL
d: Logarithm of period of activity of the sample since its establishment until now
e: Logarithm of total assets
f: Type of ownership: public, semi-public (private) and private
g: The sum of revenues of the sample to the sum of revenues of the banking system to the power of two

A2: Descriptive Statistic

Variable	Min	Max	Range	Mean	Std.Dev.	Median	Skewness	Kurtosis
x_1	-2147.68	104.78	2252.46	15.1111	82.37598	16.9727	-24.759	647.672
x_2	.20	2.42	2.22	.9883	.21761	1.0173	-.702	6.046
x_3	-1.37	45.94	47.31	.6953	3.87020	.1253	9.641	103.571
x_4	0.00	.39	.39	.1296	.07529	.1184	.839	.476
x_5	0.00	.52	.52	.0423	.05790	.0223	3.296	14.450
x_6	0.00	.36	.36	.0452	.04975	.0266	2.791	10.846
x_7	0.00	.70	.70	.0975	.08917	.0755	1.856	5.345
x_8	.00	.18	.18	.0450	.03009	.0365	1.501	2.646
x_9	.01	.74	.74	.0913	.07998	.0689	3.686	20.954
x_{10}	-.58	14.96	15.54	.1057	.60716	.0565	20.332	489.440
x_{11}	.19	1.08	.89	.7681	.15726	.7851	-1.143	1.390
x_{12}	-.08	.81	.89	.2319	.15726	.2149	1.143	1.390
x_{13}	.00	.18	.17	.0397	.01881	.0386	1.741	8.882
x_{14}	.01	5.73	5.72	.9743	1.03733	.6148	1.827	3.611
x_{15}	.01	1.44	1.42	.2649	.23228	.2115	1.671	3.210
x_{16}	.24	.90	.66	.5977	.10415	.5964	.102	.992
x_{17}	-42.83	101.40	144.23	2.3975	8.19638	1.9336	5.277	64.176
x_{18}	.03	1.84	1.81	.3775	.25181	.3659	1.863	7.425
x_{19}	.00	.19	.18	.0558	.03484	.0479	1.078	1.074
x_{20}	0.00	.74	.74	.1586	.10103	.1383	1.834	6.086
x_{21}	0.00	.35	.35	.0405	.06171	.0193	3.152	9.758
x_{22}	0.00	.25	.25	.0385	.03631	.0246	2.001	4.933
x_{23}	0.00	.58	.58	.0796	.06194	.0715	2.362	11.492
x_{24}	.00	2.82	2.82	.1897	.31581	.0886	4.371	24.049
x_{25}	986.00	17803.0	16817	3320.85	2708.1325	2354.000	2.380	5.720
x_{26}	1204.00	86583.0	85379	6321.65	10503.338	3012.000	4.282	20.251
x_{27}	.02	.69	.68	.2712	.12068	.2607	.433	.842
x_{28}	.03	2.26	2.24	.4211	.29919	.3530	2.366	8.806
x_{29}	.01	1.13	1.12	.1707	.11338	.1419	2.092	8.849
x_{30}	-.33	.03	.36	.0007	.02993	.0025	-9.026	88.504
x_{31}	-.07	.01	.08	.0012	.00781	.0011	-5.668	44.189
x_{32}	-2.07	23.98	26.04	.0628	.93745	.0187	23.131	580.259
x_{33}	-4.21	35.59	39.79	-.2614	1.65828	-.2399	16.566	330.019
x_{34}	-.10	.07	.17	.0034	.02392	.0057	-1.099	2.953
x_{35}	-4.72	2.90	7.62	.0376	.74259	.1215	-1.603	7.898
x_{36}	-3.15	.56	3.70	.0224	.33214	.0407	-7.376	63.585
x_{37}	-6.78	10.54	17.32	.2311	1.69779	.1136	1.547	15.293
x_{38}	-.11	.02	.13	.0016	.01119	.0019	-6.771	57.919
x_{39}	-3.39	55.05	58.43	.0658	2.06518	.0251	25.719	684.374
x_{40}	-.08	.80	.88	.0905	.09220	.0716	3.430	18.532
x_{41}	-.07	.78	.85	.0737	.09238	.0471	3.631	18.770
x_{42}	.03	30.91	30.88	2.8318	4.12849	1.1095	2.840	10.235
x_{43}	0.00	.08	.08	.0209	.01399	.0186	1.106	1.684
x_{44}	-111.73	18.12	129.85	3.6928	5.62895	2.7620	-11.627	241.277
x_{45}	-.77	.64	1.41	.0937	.10822	.0659	1.164	12.948
x_{46}	-35.81	24.20	60.01	-2.4323	6.08055	-.5277	-1.998	9.158
x_{47}	-1.39	4.52	5.91	3.1164	.85847	3.2935	-.375	.214
x_{48}	15.95	21.65	5.70	19.2638	1.19554	19.3325	-.380	-.430
x_{49}	1.00	3.00	2.00	1.9444	.84859	1.9167	.106	-1.604
x_{50}	0.00	.17	.17	.0488	.03145	.0426	.953	.641

A2: Descriptive Statistic

Variable	Min	Max	Range	Mean	Std.Dev.	Median	Skewness	Kurtosis

A3: KMV-Merton Models Coefficients [a]

Merton	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower	95.0% Confidence Interval for B Upper	Collinearity Statistics Tolerance	Collinearity Statistics VIF
constant	-.665	.258		-2.583	.010	-1.171	-.160		
X_1	-.005	.001	-1.784	-4.649	.000	-.006	-.003	.004	275.199
X_2	-.008	.086	-.008	-.094	.925	-.176	.160	.067	14.933
X_3	-.002	.003	-.036	-.601	.548	-.008	.004	.153	6.521
X_4	.634	.332	.229	1.908	.057	-.018	1.286	.037	26.943
X_5	.106	.304	.029	.349	.727	-.490	.702	.075	13.324
X_6	.179	.299	.043	.600	.549	-.408	.766	.105	9.542
X_7	-.572	.201	-.245	-2.844	.005	-.966	-.177	.072	13.852
X_8	-1.433	.281	-.207	-5.094	.000	-1.985	-.881	.324	3.088
X_9	-.139	.221	-.053	-.627	.531	-.572	.295	.074	13.466
X_{10}	.014	.008	.040	1.609	.108	-.003	.030	.885	1.130
X_{12}	-.144	.055	-.109	-2.602	.009	-.253	-.035	.306	3.264
X_{13}	-.395	.461	-.036	-.857	.392	-1.299	.510	.309	3.237
X_{14}	-.031	.013	-.152	-2.281	.023	-.057	-.004	.121	8.295
X_{15}	-.049	.068	-.055	-.730	.466	-.182	.083	.094	10.627
X_{16}	-.100	.092	-.050	-1.087	.277	-.282	.081	.251	3.990
X_{17}	-.002	.001	-.068	-2.455	.014	-.003	.000	.695	1.439
X_{18}	-.141	.059	-.171	-2.412	.016	-.257	-.026	.106	9.397
X_{19}	.081	.398	.014	.203	.839	-.700	.861	.121	8.272
X_{21}	-.207	.339	-.061	-.611	.541	-.874	.459	.053	18.917
X_{22}	-.343	.440	-.060	-.781	.435	-1.206	.519	.091	10.975
X_{23}	.370	.407	.110	.911	.363	-.428	1.169	.037	27.351
X_{24}	-.103	.028	-.157	-3.641	.000	-.159	-.048	.290	3.454
X_{25}	-1.239E-6	.000	-.016	-.192	.848	.000	.000	.076	13.240
X_{26}	2.777E-6	.000	.140	2.372	.018	.000	.000	.153	6.518
X_{27}	.125	.191	.073	.656	.512	-.250	.501	.044	22.960
X_{28}	.023	.067	.033	.337	.736	-.109	.155	.057	17.442
X_{29}	.130	.060	.071	2.163	.031	.012	.247	.503	1.988
X_{30}	5.870	1.622	.844	3.620	.000	2.686	9.053	.010	101.502
X_{31}	1.239	8.376	.047	.148	.882	-15.207	17.685	.005	184.638
X_{32}	.299	.059	1.348	5.083	.000	.184	.415	.008	131.401

A2: Descriptive Statistic

Variable	Min	Max	Range	Mean	Std.Dev.	Median	Skewness	Kurtosis	
X_{33}	-.077	.016	-.617	-4.743	.000	-.110	-.045	.032	31.638
X_{34}	1.754	.598	.201	2.934	.003	.580	2.928	.114	8.810
X_{35}	-.016	.018	-.055	-.870	.385	-.051	.020	.132	7.561
X_{36}	-.003	.159	-.004	-.017	.987	-.314	.309	.008	119.616
X_{37}	.001	.003	.010	.374	.709	-.005	.008	.741	1.350
X_{38}	-16.550	6.131	-.889	-2.699	.007	-28.587	-4.512	.005	202.782
X_{39}	-.247	.046	-2.451	-5.321	.000	-.338	-.156	.003	396.529
X_{40}	.905	1.768	.401	.512	.609	-2.567	4.376	.001	1145.74
X_{41}	-.938	1.760	-.416	-.533	.594	-4.393	2.518	.001	1139.39
X_{42}	-.001	.002	-.022	-.596	.552	-.005	.003	.387	2.586
X_{43}	-1.997	1.666	-.134	-1.199	.231	-5.268	1.274	.043	23.431
X_{44}	.003	.004	.080	.749	.454	-.005	.011	.047	21.390
X_{45}	.041	.177	.021	.231	.818	-.306	.388	.063	15.773
X_{46}	.001	.001	.031	1.064	.288	-.001	.003	.618	1.619
X_{47}	.054	.017	.225	3.189	.001	.021	.088	.108	9.268
X_{48}	.068	.014	.389	4.968	.000	.041	.094	.087	11.447
X_{49}	-.134	.016	-.544	-8.424	.000	-.165	-.102	.128	7.807
X_{50}	.527	.345	.080	1.529	.127	-.150	1.203	.198	5.060

a. Dependent Variable: PD_MERTON

A4: Z-Score Models Coefficients [a]

Z-Score	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Lower	Upper	Tolerance	VIF
constant	.252	.161		1.565	.118	-.064	.567		
X_1	.000	.001	.236	.705	.481	-.001	.002	.004	275.199
X_2	-.185	.053	-.270	-3.462	.001	-.290	-.080	.067	14.933
X_3	-.009	.002	-.231	-4.468	.000	-.013	-.005	.153	6.521
X_4	-.738	.207	-.373	-3.560	.000	-1.145	-.331	.037	26.943
X_5	-.037	.190	-.014	-.194	.846	-.409	.335	.075	13.324
X_6	.029	.187	.010	.157	.875	-.337	.396	.105	9.542
X_7	.063	.126	.038	.502	.616	-.183	.310	.072	13.852
X_8	.298	.176	.060	1.699	.090	-.046	.643	.324	3.088
X_9	-.187	.138	-.100	-1.352	.177	-.457	.084	.074	13.466
X_{10}	.001	.005	.004	.206	.837	-.009	.011	.885	1.130

A2: Descriptive Statistic

Variable	Min	Max	Range	Mean	Std.Dev.	Median	Skewness	Kurtosis	
X_{12}	.029	.035	.030	.835	.404	-.039	.097	.306	3.264
X_{13}	.156	.288	.020	.541	.589	-.409	.720	.309	3.237
X_{14}	-.037	.008	-.256	-4.394	.000	-.053	-.020	.121	8.295
X_{15}	.246	.042	.384	5.834	.000	.163	.329	.094	10.627
X_{16}	.032	.058	.022	.555	.579	-.081	.145	.251	3.990
X_{17}	4.213E-5	.000	.002	.096	.924	-.001	.001	.695	1.439
X_{18}	-.059	.037	-.099	-1.606	.109	-.131	.013	.106	9.397
X_{19}	.150	.248	.035	.605	.545	-.337	.638	.121	8.272
X_{21}	.725	.212	.300	3.420	.001	.309	1.141	.053	18.917
X_{22}	.644	.274	.157	2.346	.019	.105	1.183	.091	10.975
X_{23}	.783	.254	.326	3.084	.002	.285	1.282	.037	27.351
X_{24}	-.004	.018	-.009	-.227	.820	-.039	.031	.290	3.454
X_{25}	-8.414E-6	.000	-.153	-2.082	.038	.000	.000	.076	13.240
X_{26}	2.497E-6	.000	.176	3.416	.001	.000	.000	.153	6.518
X_{27}	.189	.119	.153	1.584	.114	-.045	.424	.044	22.960
X_{28}	-.036	.042	-.072	-.854	.393	-.118	.047	.057	17.442
X_{29}	.002	.037	.002	.065	.948	-.071	.076	.503	1.988
X_{30}	3.088	1.012	.621	3.050	.002	1.100	5.076	.010	101.502
X_{31}	33.140	5.230	1.740	6.337	.000	22.872	43.409	.005	184.638
X_{32}	-.038	.037	-.238	-1.027	.305	-.110	.034	.008	131.401
X_{33}	-.006	.010	-.066	-.581	.561	-.026	.014	.032	31.638
X_{34}	.841	.373	.135	2.254	.025	.108	1.574	.114	8.810
X_{35}	-.021	.011	-.105	-1.883	.060	-.043	.001	.132	7.561
X_{36}	-.452	.099	-1.009	-4.565	.000	-.646	-.258	.008	119.616
X_{37}	.000	.002	-.004	-.183	.855	-.004	.004	.741	1.350
X_{38}	-14.735	3.828	-1.107	-3.849	.000	-22.251	-7.219	.005	202.782
X_{39}	.012	.029	.164	.408	.683	-.045	.069	.003	396.529
X_{40}	4.430	1.104	2.744	4.013	.000	2.263	6.598	.001	1145.744
X_{41}	-4.228	1.099	-2.624	-3.847	.000	-6.385	-2.070	.001	1139.392
X_{42}	.000	.001	.014	.417	.677	-.002	.003	.387	2.586
X_{43}	-3.775	1.040	-.355	-3.629	.000	-5.817	-1.732	.043	23.431
X_{44}	-.012	.002	-.440	-4.709	.000	-.016	-.007	.047	21.390
X_{45}	.833	.110	.606	7.551	.000	.617	1.050	.063	15.773
X_{46}	-.001	.001	-.047	-1.824	.069	-.002	.000	.618	1.619
X_{47}	.031	.011	.179	2.911	.004	.010	.052	.108	9.268

A2: Descriptive Statistic

Variable		Min	Max	Range	Mean	Std.Dev.	Median	Skewness	Kurtosis	
	X_{48}	.025	.009	.202	2.953	.003	.008	.042	.087	11.447
	X_{49}	-.024	.010	-.139	-2.465	.014	-.044	-.005	.128	7.807
	X_{50}	.454	.215	.096	2.108	.035	.031	.876	.198	5.060

a. Dependent Variable: PD_ Z-Score

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