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Using Altman Z-Score to Assess the Financial Effects of Multiple Loans on SMEs

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ABSTRACT

We examine financial statements from 102 SME firms with multiple loans in order to verify whether multiple loans significantly affect financial health of SMEs. These SMEs are drawn from Iringa, Tanzania. The intended contribution of this research is the practical applications of the methods and findings which would serve as a guide for risk assessment by lending institutions, and performance bench marking for SMEs. The methodology employed in this research relies on parametric and nonparametric tests. The Altman Z-test for firm's financial distress was used as the standard tool to assess SMEs financial performance. Other methods, such as Springate modified Z, Fulmer F-score and Legault CA-score were employed as comparative measures. The finding shows that multiple borrowing had significantly moved a number of firms from Altman's "safe zone" to the "gray zone"; however the effect size under Cohen's *d* is 0.49.

Key words: Financial distress, SME, multiple loans.

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1.0 INTRODUCTION

SME definition varies across and within countries. In Tanzania, SME refers to small and medium-sized enterprises in non-farming sector, which include manufacturing, mining, commerce and services (URT, 2003). The definition categorizes SMEs according to number of employees and capital invested (between Tanzanian shillings 5,000,000 and 800,000,000) (URT, 2003). About 54% of all SMEs in Tanzania are found in the rural area (Finscope Survey, 2012).

The success or failure of SME depends on access to finance, especially from commercial banks (Mori and Richard, 2012). SMEs are perceived as high risk by banks (Mori and Richard, 2012). As the result, the government of Tanzania allowed the private sector to establish microfinance institutions (MFIs) in the mid 1990's in order to help financing small businesses. Such MFIs share a common attitude that provision of microfinance services can accelerate growth and development (Kessy and Urio, 2006). This government financial sector reform decision led to the rapid growth of demand for SMEs borrowers and MFI lenders (URT, 2001, 2003).

The growth in demands for loans led to competition among existing or new MFIs; consequently, sharing of information about borrowers in a common database or

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credit bureau becomes a difficult (Chalu and Lubawa, 2014). Every MFI tries to maximize wealth by acquiring new borrowers or by creating loan portfolio that allow existing borrowers to apply for additional lending. As the result SMEs undertake multiple loans. Multiple borrowings in Tanzania are common practice (Finscope Survey, 2012; Mpogole *et al.*, 2012; Chalu and Lubawa, 2014).

Multiple loans generally occurred in a more developed credit market where borrowers may carry multiple loans or mortgages (Schicks and Rosenberg, 2011). However, in Tanzania, the cause for multiple loans is information asymmetry among lenders; lenders do not have full information about the borrower's credit portfolio (Calice et al., 2012; Chalu and Lubawa, 2014). The closing of Meridian BIAO Bank and the Tanzania Housing Bank (THB) in 1990s, i.e. 1995/1996, the National Bank of Commerce (NBC) and the Cooperative and Rural Development Bank (CRDB) combined wrote off loans equivalent to Tshs 122 billion (US$ 112 million) (IMF, 1999) attest to the problem. These closures are indications that there is a lack of proper credit risk management system in the financial sector in Tanzania. One possible reason for information asymmetry might be the weaknesses in collecting relevant information on borrowers to help create credit screening. Poorly compiled records coupled with inability of SMEs to properly express their knowledge about business opportunities (Olomi, 2009), unreliable financial plans and records (Temu, 1998), lack of adequate and reliable collateral, and lack of risk management tool (Satta, 2003; 2006) contribute to non-performing loans (NPL).

The literature on the effect of multiple loans presents inconsistent findings. Chalu and Lubawa (2014) showed that multiple loans positively affect the firm's performance. Other studies, such as Mpogole *et al.* (2012) claims that multiple loans adversely affect the firm's financial performance. In an attempt to reaffirm past studies, Chalu and Lubawa (2015) published a finding that multiple loans significantly affect SME's liquidity, profitability, leverage, and efficiency. In light of these inconclusive findings in the literature, this paper attempts to revisit the issue with the use of the Altman Z score for measuring financial distress of a firm under financial obligations of multiple loans. Financial distress arises when a firm fails to meet its financial obligations (Mumford, 2003). The Altman Z score is an indicator of financial distress; thus, it is used as a proxy for SMEs' potential financial distress under multiple loans.

Financial distress analysis generally looks at publicly traded companies. These public companies have data available online. However, SMEs do not share their financial information with the public. Thus, there is a gap in data accessibility for SMEs financial distress studies. This gap makes the study of financial distress among SMEs more difficult. This study makes several contributions to the field of financial management of SMEs in developing economies. There is an inadequate literature concerning the effect of multiple loans on SME's performance in developing economies. This research attempts to fill that gap. Secondly, although prior publications discourage multiple loans as over-borrowing and counter productive to the firm's performance and exposing the firm to the risk of bankruptcy, the finding of this research points to a different direction. Multiple loans are not adverse to firm's performance or increase the risk of bankruptcy. Third, this research shows that the Altman Z-Score model could also be used to analyze financial distress of SMEs in developing economies, such as Tanzania. Tanzania is a case study that could serve as a useful lesson for other developing economies.

2.0 LITERATURE REVIEW

The literature shows the usefulness of financial ratios to predict the firm's financial distress. The earlier work of Beaver (1966) indicated that financial ratios could predict the likelihood of firm's failure. Subsequently, there have been studies using financial ratios derived from firm's financial statements to predict the likelihood of financial distress. For instance, Altman (1968) developed multivariate statistical model by using financial ratios to discriminate failure from non-failure. Ohlson (1980) uses financial ratios to develop the logit model to predict business failure with a sample of 105 bankrupt firms and 2,058 non-failing firms. While Altman, Haldeman, and Narayan (1977) found that Return on Assets (ROA) to be a significant ratio to explain corporate failure, Izan (1984) also found that Return on Equity (ROE) is also useful in identifying failed companies. A study by Dambolena and Khoury (1980) suggested that the debt ratio is one of the better predictors in discriminant function.

Other studies by Altman, Haldeman and Narayanan (1977), McGurr and Devaney (1998), Charalambous, Charitou and Kaourou (2000), Laitinen and Laitinen (2000), Parker, Peters and Turetsky (2002), Platt and Platt (2002) found the usefulness of current ratio in predicting corporate failure. Laitinen and Laitinen (2000) and Laitinen (2005) also found that quick ratio (current assets minus inventories, then divide by current liabilities) is significant in determining financial distress. Lakshan and Wijekoon (2013) suggested three financial ratios: working capital to total assets, debt ratio and cash flow from operating activities to total assets. This appears to show more explanatory power to predict corporate failure. Nyamao et al. (2013) uses financial ratios and then Altman model to analyze the liquidity, solvency and financial health of SMEs in Kenya. By using financial ratios Chalu and Lubawa (2015) identified that multiple loans have significant effects on SMEs' liquidity, profitability, leverage and efficiency effects. Li (2015) used financial ratios to determine the accuracy of Altman's Z-score model consumer goods companies in the United Kingdoms (UK) with comparison to the accuracy claimed by Altman.

2.1 Altman's Z-score Model

Financial distress studies may be called "bankruptcy prediction studies." These studies employed parametric model using the firm's financial statements as the basis. Three models are exemplary: (i) Altman Z-score in 1968 (ii) Springate's modified Z score in 1978, (iii) Fulmer's index in 1984, and (iv) CA-Score method developed by Jean Legault in 1987.

The Altman Z-score is used to gauge financial distress of a firm. It is used to forecast the firm's potential bankruptcy. The formal structure of Altman Z-score is given by:

$$Z = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \quad (1)$$

where X_1 = working capital/asset; X_2 = retained earnings/asset; X_3 = EBIT/total assets; X_4 = market value of equity / total assets; X_5 = sales/total assets; Z = overall index; and β_i = parameter to be estimated (Altman, 1962 & 2000).

Altman (1968) applied the model to a sample of manufacturing companies in the US. Subsequent studies reaffirmed the applicability of the Z-Score model to privately held companies (Deakin, 1972; Ohlson, 1980), non-manufacturing firms (Grice and Ingram, 2001; Altman, 2000), banks (Sinkey, 1975; Chotalia, 2014), insurance companies (Trieschmann and Pinches, 1973; Pinches and Trieschmann, 1977). Further, the Altman score model proved to be useful to small business in identifying bankruptcies (Edmister, 1972; Plandor and Landryov, 2012; Altman *et al.*, 2008; Jahur and Quadir, 2012; Nyamao *et al.*, 2013; Lin, 2015). The Altman Z score has a wider application since its introduction and its revised version of 1983 by including private companies. However, the Altman Z-score model has not been applied to SMEs in developing economies. This research is the first of such an attempt. Few studies in Tanzania concentrated on the application of Altman Z-score model in banking sector (Chijoriga, 2000; Chijoriga, 2011). This paper examines 102 companies in non-manufacturing sector.

Altman's research identified five key ratios to predict failure and the model expresses these ratios in the form of a relationship with other ratios in the model with assigned a relative weighting. The bankruptcy score sorts firms into bankrupt and non-bankrupt groups according to their Z score (Aziz *et al.*, 2006). In 1968, the Altman Z-score model was parametized as:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \tag{2}$$

The model was later modified (Altman, 1983, p. 122) to cover private firms as:

$$Z' = 0.717X_1 + 0.84T_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \tag{3}$$

The decision rule is governed by: $Z' > 2.99$ means "safe;" $1.10 < Z < 2.60$ means "gray area" and $Z < 1.11$ means that the firm is in financial distress.

In 1982, the Altman Z-score underwent a third improvement to cover non-manufacturing companies (Altman, 1982, p. 124). The third version of the Altman Z score is given by:

$$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \tag{4}$$

For non-manufacturing firms, the safe zone is defined as $Z > 2.60$; the gray area is $1.10 < Z < 2.60$ and financial distress is defined as $Z < 1.10$. The model had an average accuracy of more than 85% in bankruptcy prediction (Aziz et al., 2006) and is still the most popular technique in business failure identification. It appears to set a standard for bankruptcy prediction models (Altman et al, 2000) and gained wide acceptance in the past two decades among auditors, management consultants, courts of law and even used in database systems for loan evaluations (Eidleman, 1995).

2.2 Springate Modified Z-Score Method

The second method to identify financial distress is called the Springate method. It is a simplified version of Atman's Z-score (Springate, 1978). The Springate method is given by:

$$Z = 1.03A + 3.037B + 0.66C + 0.40D \tag{5}$$

where A = Working Capital/Total Assets; B = Net Profit before Interest and Taxes (NPBIT)/Total Assets; C = Net Profit before Taxes (NPAT) / Current Liabilities and D = Sales/Total Assets. The decision rule states that if Z < 0.862; then the firm is classified as "failed." Springate is said to have been able to predict with 83% accuracy.

2.3 Fulmer's F-Index Method

In 1984, Fulmer introduced a third method (Fulmer, 1984). The Fulmer method uses 9 ratios as the predictive variables. The Fulmer's F-index is given by:

$$F = 5.52\ X1+.212\ X2+.073\ X3+1.27\ X4-.12\ X5+2.335\ X6+.575\ X7+1.082\ X8+.894\ X9-6.075 \tag{6}$$

where F: total index; X1: accumulated profits ratio to total assets; X2: the ratio of sales to total assets; X3: the ratio of profit before taxation to owners' equity; X4: the ratio of operational cash flows to total liabilities; X5: the ratio of liability to total assets; X6: the ratio of current liability to total assets; X7: total logarithm of tangible assets; X8: the ratio of flowing capital to total liabilities; and X9: the ratio of logarithm before interest and tax to interest cost. The decision rule states that if F<0, the company is classified as a bankrupt firm. The Fulmer methods is said to be 98% accurate for forecasting within one year and 81% accurate predicting bankruptcy in more than one year.

2.4 Legault CA-Score Method

A fourth method for predicting firm bankruptcy is called the CA-Score method developed by Jean Legault (Legault, 1987). The CA-Score method is given by:

$$\text{CA-Score} = 4.5913A + 4.5080B + 0.3936C - 2.7616 \tag{7}$$

where, A = Shareholders investment / Total assets B = Earnings before taxes and extraordinary items + Financial expenses / Total assets C = Sales / Total assets. The decision states that if CA-Score < -0.03; then the firm is called as "failed." This method produces a reliability rate of 83%.

2.6 Financing patterns for SMEs

Capital structure is the mix of a firm's non-current liabilities (or permanent – long term-debt) and equity. According to International Accounting Standard number 39(IAS 39), long-term debt is capital from lenders such as commercial banks and has to be repaid. In contrast, equity represents capital contributed by owners of the business. Both long-term debt and equity have costs. No free capital is available in the market. However, in designing an optimal capital structure maximize value of the firm, Weighted Average Costs of Capital (WACC) is employed. The WACC incorporates cost of the various sources of non-current liabilities and equity. The definition of capital structure is applicable to all firms regardless of size. In general, WACC is given as:

$$WACC = \frac{\sum_{i=1}^{N} r_i MV_i}{\sum_{i=1}^{N} MV_i} \tag{8}$$

where N = number of sources of capital; r_i = required rate of return of the security *i*; MV_i = market value of all outstanding security *i*. Where the choice of capital structure is comprised of debt and equity, WAAC with tax effect is given by:

$$WACC = \left(\frac{MV_e}{MV_d + MV_e}\right) R_e + \left(\frac{MV_d}{MV_d + MV_e}\right) R_d (1-t) \tag{9}$$

where MV_d = market value of outstanding debt; MV_e = market value of outstanding equity; R_e = cost of equity; R_d = cost of debt; and t = tax rate Cohen (1992), Olejnik & Algina (2003) and Steiger (2004). Both general WACC and WACC with tax effect would not be an efficient tool for capital structure analysis in a business environment where access to capital is limited. The distinction between financing by debt and equity is meaningful if the firm could access the capital market and has the opportunity to choose between debt or equity. In Tanzania, as in other parts of the world where access to capital is limited, conventional tool for capital structure selection such as WACC may not be useful unless it is modified to fit SMEs' circumstances. Since SMEs have no equity cost, i.e. issuing stocks to outside investors, WACC is reduced to:

$$WACC_{sme} = R_d(1-t) \tag{10}$$

Since there is no equity cost from outside investor ($MV_e = 0$) where $[WV_d / (WV_d + MV_e)]$. If there are multiple loans, the aggregate costs of capital become:

$$WACC_{sme} = \frac{1}{n}\sum_{i=1}^{n}\left(R_d(1-t)\right)_i \tag{11}$$

The number of loans undertaken by SMEs could be explained by the optimal debt level under the Pecking Order Theory.

2.6.2 Pecking Order Theory in Capital Structure

The Pecking Order Theory (POT) ranks the preferred order of financing. According to POT, the firm tries to utilize its internal financing sources first (i.e. retained earnings) then financing by debt. Equity is reserved as a last resort. The key principle of POT is in conformity with the signaling theory where the presence of asymmetric information and the need to incur costs of new issues. Cosh and Hughes (1994) argued that POT can be easily applied in small and medium sized firms due to opaqueness and adverse selection problems they face which in turn lead to credit rationing and cause them to bear high information costs. A study by Coleman and Cohn (2000) also confirmed the applicability of POT to small and privately held firms where the information asymmetries are common. Wu, Song, and Zeng (2008), showed the contribution of POT in studying SMEs financing.

According to POT, high growth firms will have higher debt ratio because managers try to avoid equity (Frank & Goyal, 2003). POT defines the order preference for financing by placing retained earning or cash on hand as the first choice of preference then follow by debt. Equity is reserved as a last resort. Under POT, the partial aggregate form of accounting cash flow identity for the flow of fund is given by:

$$DEF_t = DIV_t + I_t \Delta W_t - C_t = \Delta D_t + \Delta C_t \tag{12}$$

where DIV_t = dividends at period *t*; I_t = investment at period *t*; ΔW_t = working capital at period *t*; C_t = cash flow after interest and tax. Shyam-Sunder and Myer (1999) showed that since equity is the least preferred source of capital, the empirical model of POT is modified to:

$$\Delta D_{iy} = a + b_{PO} DFF_{it} + e_{it} \tag{13}$$

where e_t = error term; a = 0 and b_{PO} = 1. Shyam-Sunder and Myer rejected POT and asserted that the relevant flow of fund is captured in the following model:

$$DEF_t^{SSM} = DIV_t + I_t + \Delta W_t + R_t - C_t \tag{14}$$

Even with this modification, POT still could not fully explain the flow of funds in SMEs because SMEs do not pay dividends. We proposed further modification by removing the dividends term to obtain:

$$DEF_t = I_t + \Delta W_t + R_t - C_t \tag{15}$$

where R_t = current position in long-tem debt in period *t*. In this bare-bone model, equity is removed, thus, POT is reduced to $DEF_t = \Delta D_t$ or $DEF_t = I_t + \Delta W_t + R_t - C_t = \Delta D_t$. In a case where the SMEs engage in multiple loans practice, the funding deficit model DEF_t may be given by:

$$DEF_t^* = \sum DEF_{t(i)} \tag{16}$$

If DEF_t^* exists, the risk of financial distress stemming from over-burden by debts may be minimized if the aggregate $\sum DEF_{t(i)}$ does not exceed the firm's debt carrying capacity. The average funding deficit DEF_t^* is $\left(\sum DEF_{t(i)}\right)/n$ which is equivalent to $WACC_{sme}$ in (11).

This paper tracks SMEs over a period of 2 fiscal years from 2011 to 2012. Although the tracking period is short, it is an appropriate span for multiple loans study. If the time is expanded, information asymmetry may dissipate due to better information collection and data management by MFI lenders. One contributing factor to the emergence of multiple loans in Tanzania is failure of MFIs to verify whether SME borrowers have existing loans. Moreover, a two-period time-span in this study also put SMEs' management skills to the test and allows us to test the hypothesis that: "multiple loans do not lead to financial distress." If this hypothesis is empirically supported, it implies that the availability of capital, at least by debt, leads to the strengthening of the firm's financial health because the availability of additional funds helps the firm to stay afloat and engage in profitable operations.

POT does not predict an optimal debt financing. While other finance theories strongly advocates for target and sound capital structure which minimizes the overall cost of capital and maximize the firm's value, POT ignores the concept of optimal debt – equity mix.

2.6.3 Optimal Debt Structure as a Theoretical Support for Multiple Loans

Optimal debt structure has two objectives: "First, there should be value when the firm is liquidated: the cost of the financial distress should be low. Second, it should discourage firms from defaulting." (Bolton and Scharfstein, 1996). The model defines two players: borrower and lender as the parties to the transaction. The borrower's expected payoffs may be defined as:

$$\theta\left[x - R_x + (1-\beta_x)y\right] + (1-\theta)\left[-R_0 + (1-\beta_0)y\right] \tag{17}$$

where R_x = payment of loan obligation; x = cash flow; β_x = probability of liquidation upon default; β_0 = lender's right to liquidate upon default; θ = probability; and y = cash flow at date 2 at $t+1$ period. This position of the borrower is contrasted with that of the lender. The lender's expected profit from the transaction is given by:

$$\theta(R_x + \beta_x L_x) + (1-\theta) + (R_0 + \beta_0 L_0) - k \tag{18}$$

where L_x and L_0 are liquidated values of assets seized by creditors in case of default by the borrower at cash flow stream x and 0. This condition is true when assets are pledged by borrower as collaterals for the loan. However, in the present case in Tanzania, as in many cases elsewhere, it is a common practice that collateral is not used in commercial loans to SMEs. Loans to SMEs may be unsecured. The loan contract is no more than a promissory note made by borrower to the lender and the decision to extend credit is made on the subjective judgment of the lending manager upon rudimentary data or information about SME owner's current cash flow, character in business and financial management, or business potential for financial sustainability. As in this study, it is the lending institutions who prepare the financial statements of SMEs in order to decide whether to extend credit. The prospect of payment depends on the pattern of cash flow and the expected future stream, without the use of collateral. Therefore, in this case following Bolton-Scharstein's approach, the payment remains R_x and cash flow x, the SME's incentive for making payment is:

$$x - R_x + (1-\beta_x)y \geq x + \beta_0 S + (1-\beta_0)y \tag{19}$$

where S = utility that the SME received from making payment R_0 when each cash flow stream is x and the lender is entitled to liquidate assets, and β_0 when the firm pays out zero.

If $R_0 = 0$, meaning SME does not making loan payment, the SME's surpluses are maximized. However, when the SME defaults, it will also face liquidation in case where the assets had been pledged as collateral or when the loan is secured the lender may still recourse to the law and seize the assets by legal mechanism; therefore, the condition $R_0 = 0$ maximized the SME's surplus, but provides no incentive. For this reason, Boltton-Scharfstein model suggests that $R_0 < 0$ where the probability of default β_0 is reduced. The incentive constraint for the SME to continue making the payment of the loan obligation is:

$$R_x \leq \beta_0(y - S) \tag{20}$$

The nonnegative profit constraint of the lender (MFIs) becomes:

$$\beta_0[\theta(y - S) + (1-\theta)L_0] - k = 0 \tag{21}$$

The corresponding payoff of the SME borrower is likewise:

$$\theta_x + y - k(1-\theta)\beta_0(y - L_0) \tag{22}$$

where $(1-\theta)\beta_0$ = probability of liquidation; $(y-L_0)$ = loss in value from liquidation; and $\theta_x + y - k$ = best case scenario where there is no default and no liquidation.

According to Bolton-Scharfstein's approach delineated above, the optimal debt level occurs when the SME expected payoff is decreasing in β_0 (or probability of default) and the lender's profit increasing in β_0. The optimal level is one which neither lender MFIs nor borrower SMEs experience unequal incentive. This ideal condition may be achieved by setting β_0 to a minimal level at:

$$\beta_0 = \frac{k}{\theta(y-S)+(1-\theta)L_0} \tag{23}$$

where $\beta_0 \leq 1$ and k is less than the maximum gross profit of creditor. That *maximum profit* occurs only when the SME is in default; thus, the maximum profit of MFIs is determined by:

$$\pi \equiv \theta(y-S)+(1-\theta)L_0 \tag{24}$$

The MFI's maximum profit is achievable only under the assumption that the assets could be seized from SMEs. Absent a pledge of collateral, this ability to seize SME's assets would depend on the strength and passion the local legal system. Statements (23) and (24) define optimal debt level.

The explanation from (17) – (24) outlines the relative position between lender (MFI) and borrower (SME). In order to appreciate the practice of multiple loans in Tanzania, we need to explore the relative benefits or efficiency of multiple loans in the lender's perspective and ask "whether multiple loans are problematic" for both SMEs and MFIs? If there is a theoretical support for multiple loans practice by lenders, then the issue of multiple loans as a result of information asymmetry between lenders and borrowers becomes moot.

Bolton and Scharfstein argues that in case of default by the borrower, lender would seize the assets through liquidation. The argument also assumes that the lender is best in lending but does not do well in managing assets. Thus, to maintain economic efficiency, it becomes necessary to have a third party to enter the transaction at time of the liquidation. This late comer is called an "outside buyer". Bolton and Scharfstein defined this outside buyer as αy where $1 < \alpha \leq 1$. By entering the transaction, the outside buyer will incur cost at "c". This cost is unknown at date "0" at the time when the outside buyer starts negotiation to buy the seized assets; however, it is expected that this cost component is distributed $[0, \bar{c}]$. Therefore, like borrower and lender who had their own incentives in the transaction, the outside buyer must maintain its cost lower than the surplus from the transaction. We know that at date 0, the expected value of the liquidation is given by:

$$L_0(1) = \frac{\alpha^2 y^2}{4\bar{c}} \tag{25}$$

However, if no outside buyer enters the transaction, the lender (MFI) and borrower (SME) splits the surplus in y as $S = y/2$.

In one creditor case, the profit of the lender is given by:

$$\pi(1) \equiv \theta\left(\frac{y}{2}\right) + (1-\theta)\left(\frac{\alpha^2 y^2}{4\bar{c}}\right) \tag{26}$$

where $\beta_0(1) = \dfrac{k}{\pi(1)}$. Boltopn and Scharfstein concluded that $\beta_0(1)$ is decreasing in θ where $(1-\theta)\beta_0(1)[y - L_0(1)]$ has low efficiency for high θ or low-default-risk, and $\beta_0(1)$ is decreasing in α and $L_0(1)$ is increasing α and inefficiency is also decreasing in α .

A second scenario deals with multiple lenders. This is a case of multiple loans. In Tanzania where multiple loans are practiced by SMEs, the loans are taken from different lenders. Although one tend to conclude that lenders are willing to lend because they do not know about existing loans carried by the SME borrower. This assumption may become naive in light of the theoretical support for lenders to turn blind eyes on the apparent "information asymmetry." Bolton and Scharfstein presented two creditors scenario by assuming that the borrower takes out a second loan to buy a second asset: (i) y^A = date 2 cash flow from asset A without asset B, (ii) y^B = date 2 cash flow from asset B without asset A, and (iii) $y - y^A - y^B > 0$ and that $y - y^A - y^B = \Delta$ where $\Delta > 0$. In this scenario, lender *a* extends credit to a loan to purchase asset A and lender *b* provides loan to purchase asset B. Recall that in case of default, there is an outside buyer to the liquidation transaction. The marginal utility of each party is determined by its Shapeley value as shown below (Shapley, 1953, pp. 307-317; and Hart, 1989; pp. 210-216):

$$U_A = \frac{1}{2}\alpha y^A + \frac{1}{3}\alpha\Delta \qquad \text{for lender } a \tag{27a}$$

$$U_B = \frac{1}{2}\alpha y^B + \frac{1}{6}\alpha\Delta \qquad \text{for lender } b \tag{27b}$$

$$U_O = \frac{1}{2}\alpha y^A - \frac{1}{6}\alpha\Delta \qquad \text{for outside buyer } O \tag{28}$$

The bargain probability of the outside buyer is given by:

$$b_O = \left(\frac{1}{\bar{c}}\right)\left(\frac{1}{2}\alpha y\right) - \frac{1}{6}\alpha\Delta \tag{29}$$

Finally, Bolton and Schafstein gives the payoff to the two creditors, in our case payoff to two lenders in multiple loans, as:

$$L_0(2) = \frac{1}{c}\left(\frac{\alpha y}{2} + \frac{\alpha\Delta}{6}\right)\left(\frac{\alpha y}{2} - \frac{\alpha y}{6}\right) \tag{30}$$

compare to a case of one creditor: $L_0(1) = \dfrac{\alpha^2 y^2}{4\bar{c}}$. This proves that two lenders receives more than one creditor if outside buyer enters the liquidation process. However, absent outside buyer, two lenders receive less. Outside buyer would be discouraged from entering the transaction if the cost *c* exceeds the surplus from the transaction. Assume that in a non-rudimentary economy, the market is adequately efficient to provide room for the outside buyer to profit from the transaction. According to Bolton-Scharfstein model, there is a theoretical support for multiple loan practice and tolerance by MFIs in Tanzania.

In a two lenders case, the SME's marginal utility is given by:

$$S(2) = \frac{y}{2} - \frac{\Delta}{6} \tag{31}$$

According to the Bolton-Schafstein model, the decision rule for multiple loan practice is given by:

$$\theta\frac{y}{2} + (1+\theta)\left(\frac{\alpha^2 y^2}{4\bar{c}}\right) < k < \theta\frac{y}{2} - (1+\theta)\left(\frac{\alpha^2 y^2}{4\bar{c}}\right) + \theta\frac{\Delta}{6} - (1-\theta)\left(\frac{\alpha^2 \Delta^2}{36\bar{c}}\right) \tag{32}$$

The interpretation of the Bolton-Scharfstein decision rule states that multiple lenders or multiple loans practice works in the favour of lenders because the surplus in case of default of borrower is greater in multiple loans (two lenders) case than it is in single loan (one lender) case. This is the theoretical support or the multiple loans by MFIs in Tanzania. Our objective is to test whether under increased loan obligation under multiple loans SMEs experience financial distress. The financial distress will be measured by the Altman Z-score.

3.0 METHODOLOGY

3.1 Geography and demography of the targeted population

The research was carried out in Kihesa, Mkwawa, Mwangata, Kitwiru, Ruaha, Mtwivila, Ilala, Makorongoni, Mivinjeni, Kitanzini, Mshindo, Gangilonga, Kwakilosa and Mlandege wards of Iringa Municipality, in Iringa Region, Tanzania. The population of Iringa Municipality as per Population and Housing Census 2002 is 106,371 with an annual growth rate of 1.6 percent. Projection of total population up to 2011 is 166,237 where by 80,293 are males and 85,944 females.

The economy of the region is predominantly SMEs engaging in small scale trade and production. The estimates Gross Domestic Product (GDP) per year using income approach based on 2008 figure is Tshs. 60,479,000,000 which provide the per capita income to be TShs. 429,440 and per day is 1,176. This amount is still under poverty line defined by 1 dollar (Tshs.1,700) per day. The average annual per capita income of Tanzania is 600.66 US dollars in 2014.[1] In Tanzania, the SME sector total wage employment amounts to 57% (Jaensson and Nilsson, 1998), while SMES contribute 35% to the country's Gross Domestic Product (Wangwe, 1999).

3.2 Study design

1 http://www.tradingeconomics.com/tanzania/gdp-per-capita.

This research is a quantitative study where 204 financial reports were collected from 102 SMEs in study area between June to December, 2013 under one-stop-visit to assure objectivity and minimize any possibility of financial data modification by SMEs. These SMEs filed annual financial reports to their lenders. A total of 204 annual financial reports were collected for financial year 2010/2011 and 2011/2012 from SMEs across a range of sector. Sample size was estimated by using the following formula (Amin, 2002).

$$n = \frac{Z^2\sigma^2}{E^2} \qquad (33)$$

where n = sample size; σ = estimated population standard deviation; and E = standard error determine by $E = \sigma / \sqrt{n}$. A data set of 10 counts was used as test sample in order to verify the minimum sample sized. Five sets of 10 elements were used to obtain the minimum sample size. The minimum sample size is 27. The total data collection in this study is 102 financial reports per year or 204 reports for the two years in this study.

We calculate the company's financial ratios by computing the liquidity indicator (X1); the Retained earnings to total assets, an indicative of the firm's age and its past profitability (X2); the Earnings before interest and tax (EBIT) to total assets, an indicative of profitability indicator(X3); the Market value of equity divided by book value of total liabilities (X4); the ratio of sales to total assets as indicatives of the asset efficiency indicator(X5) and Zn is the Overall index for both financial years (before acquiring and after acquiring multiple loans). Then the overall index Z_n was used to classify the SMEs to bankruptcy risk.

4.0 FINDINGS

4.1 Altman's Z Score Findings

There are three types of Altman Z-score. The results of the calculation under these three methods are presented in Tables 2 and 3. The original Altman Z-score were originally used with publicly traded companies. Due to the financing choice and capital structure available to publicly traded companies, the original Z-score would not be applicable to SME analysis. The results Altman Z-score for non-manufacturing firms show no information since there are no changes between *before* and *after* multiple loans. The reading of the Z-score for private firms is informative.

Table 2. Results of Three Methods of Altman Z-Score *BEFORE* Multiple Loans

Type of Altman Z Score	Safe Zone	Gray Zone	Distress
$Z_{original}$	$Z \geq 2.99$* **0****	$1.81 < Z < 2.99$ **18**	$Z < 1.81$ **84**
$Z_{private}$	$Z \geq 2.99$ **88**	$1.23 < Z < 2.99$ **14**	$Z < 1.23$ **0**
Z_{nonMFR}	$Z \geq 2.60$ **102**	$1.10 < Z < 2.60$ **0**	$Z < 1.11$ **0**

*Altman Z Score. ** Number of firms.

Fore the acquisition of multiple loans, there were 88 SMEs in the "safe zone" for $Z_{private}$ and 14 SMEs were in the "gray zone." No firms were in the distress situation. These numbers are compared to the *after* the acquisition of multiple loans in

Table 3. The number of firms remained in the "safe zone" is reduced from 88 to 54 firms and the number of firms in the "gray zone" increased from 14 to 48. We are faced with the question of "whether this change is a significant effect size?"

Table 3. Results of Three Methods of Altman Z-Score *AFTER* Multiple Loans

Type of Altman Z Score	Safe Zone	Gray Zone	Distress
$Z_{original}$	$Z \geq 2.99$ **0**	$1.81 < Z < 2.99$ **7**	$Z < 1.81$ **95**
$Z_{private}$	$Z \geq 2.99$ **52**	$1.23 < Z < 2.99$ **48**	$Z < 1.23$ **2**
Z_{nonMFR}	$Z \geq 2.60$ **102**	$1.10 < Z < 2.60$ **0**	$Z < 1.11$ **0**

We present the Altman Z-score in three scenarios in order to put Tanzania's case in perspective. However, the application score for Tanzania SMEs is the $Z_{private}$ results. The calculation consists of two parts: (i) means difference analysis, and (ii) Cohen's *d* effect size determination. The mean difference was determined by:

$$T = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{S\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{34}$$

The result shows that the $T_{obs} = 6.50$ which is higher than the theoretical value of 1.65. The change resulted from the number of SMEs from 88 firms in the "safe zone" to 52 firms and an increase in the "gray zone" from 14 to 48 firms are statistically significant.

Table 4A Means Difference in BEFORE and AFTER Altman Z Score

Type of Altman Z Score	$\bar{X}_{before}$	$\bar{X}_{after}$	μ_{before}	μ_{after}	SS_{before}	SS_{after}
$Z_{original}$	1.28	0.86	1.19	0.78	0.30	0.22
$Z_{private}$	5.51	3.56	4.70	3.14	25.22	6.61
Z_{nonMFR}	16.48	11.58	14.45	10.67	156.37	31.36

Table 4B Means Difference in BEFORE and AFTER Altman Z Score

Type of Altman Z Score	$SS_1 + SS_2$	$\frac{SS_1 + SS_2}{n_1 + n_2 - 2}$	S	A $\bar{X}_1 - \bar{X}_2$	B $\mu_1 - \mu_2$	$A - B$
$Z_{original}$	0.55	0.003	0.05	0.42	0.41	0.01
$Z_{private}$	31.83	0.16	0.40	1.95	1.56	0.39
Z_{nonMFR}	187.73	0.93	0.96	4.90	11.31	-7.31

Table 4C Means Difference in BEFORE and AFTER Altman Z-Score

Type of Altman Z Score	$S\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}$	$T=\frac{(\bar{X}_1-\bar{X}_2)-(\mu_1-\mu_2)}{S\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}}$	Decision Rule $H_0: T \le 1.64$ $H_{A}: T > 1.64$
$Z_{original}$	0.007	1.42	Not significant
$Z_{private}$	0.06	6.50	Significant
Z_{nonMFR}	0.13	56.23	Significant

The difference in performance among the treatment and control group is verified by the effect size. This paper employs Cohen's *d* to determine the effect size Cohen (1992), Olejnik & Algina (2003) and Steiger (2004). Effect size confirmation under Cohen's *d*:

$$d=\frac{\bar{X}_1-\bar{X}_2}{S} \tag{35}$$

where $S_1^2=\frac{1}{n_1-1}\sum_{i=1}^{n_1}\left(X_{1i}-\bar{X}_1\right)^2$ and $S_2^2=\frac{1}{n_2-1}\sum_{i=1}^{n_2}\left(X_{2i}-\bar{X}_2\right)^2$

Table 5. Effect Size Measure under Cohen's *d*

Type of Altman Z Score	$\bar{X}_{before}$	$\bar{X}_{after}$	S_1^2	S_2^2	S	d
$Z_{original}$	1.28	0.86	0.30	0.22	0.51	0.82
$Z_{private}$	5.51	3.56	25.22	6.61	3.99	0.49
Z_{nonMFR}	16.48	11.58	156.37	31.36	9.69	0.51

The effect size is not significant. Multiple loans do not have significant effect on SME's financial health. There are two firms that experienced financial distress. The DeMoivre-Lapace Theorem was used to verified whether this one case of distress is statistical significant. The DLT is given by;

$$\lim_{n\to\infty}\Pr\left[a<\frac{X-np}{\sqrt{npq}}<b\right]\le\Phi(Z_\theta) \tag{36}$$

where the theoretical value of 0.95 confidence interval for *Z* is $\Phi(Z_\theta)=1.65$; thus, the test statistic for the one distressed firm is:

$$Z=\frac{X-np}{\sqrt{npq}} \tag{37}$$

The calculation shows that $p = (s+1)/(n+2) = 3/104 = 0.03$ and $q = 0.97$. The value for Z is -0.6436 or 0.2578 or 25.78% probability. Thus, the occurrence of two financially distressed SMEs after multiple loans is not statistically significant.

5.0 DISCUSSION AND IMPLICATIONS

The use of Altman's Z-score as a tool for financial assessment must be employed with cautioned. There are three different Altman Z-score; each is used for different types of firms. The original study of Altman involved publicly traded companies in the more developed economies. The second Altman Z-score is modified to fit the profile of privately held firms. Lastly, the third type of the Altman Z-score is used for non-manufacturing firms. While the standard for classification of "safe zone," "gray zone" and "distress zone" may be similarly scaled, their coefficient for each parameter are different. The present study used the Altman Z-score for the privately held firms as the standard for evaluation.

Multiple loans have theoretical support in the literature. This paper follows the approach explained by Bolton-Scharfstein which claims that lenders stands to gain more in case of default when there are multiple lenders. At a practical level, it makes sense for SMEs to undertake multiple loans since these firms are cash poor. However, more loans or the availability of capital does not guarantee financial success. Successful management of resources comes from effective management. The needs for effective management skills among SMEs are keen in developing economies.

The implication of the findings points to a need for policy to support multiple loans practice among microfinance institutions. With an increase in loan payment burden, some firms may need time to adjust to the new financial obligations. However, the availability of additional funds may in the long run lead to more productive operations. The combined results of the mean difference analysis and Cohen's *d* effect size measurement provide a cautious optimism in our finding. The practical question of whether multiple loans are good for SMEs ultimately rests upon the lender's ability to assess credit worthiness of individual borrowers. In a country, such as Tanzania, where 35% of the GDP comes from SMEs, financing SMEs' operations is a matter of national interests and economic security.

6.0 CONCLUSION AND IMPLICATIONS

After one year, the result of multiple loans on the financial health of SME firms in Tanzania has contributed to the significant movement of firms migrating from the Altman's Z score "safe zone" to the "gray zone." Since the tracking comes from two fiscal years, it is not clear whether the change is due to financial difficulty as the result of increased financial burden or firms are making adjustment to the new loan portfolio. However, the measurement of the effect size under Cohen's *d* method shows that there is no significant adverse effect from multiple loans. In order to be more certain, the study period needs to be extended.

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APPENDIX

Table 1

Degree of Financial Distress in Sample SMEs before Multiple Loans (Group-1)

Samples	X_1	X_2	X_3	X_4	X_5	Z_n	Prediction	Score
Sample-1	0.8855	0.0891	0.4069	7.4105	1.628	8.6	Unlikely	1.00
Sample-2	0.8944	0.0982	0.407	7.442	1.682	8.7	Unlikely	1.00
Sample-3	0.6996	0.0851	0.193	5.2661	0.7721	5.53	Unlikely	1.00
Sample-4	0.9634	0.0976	0.2988	44.734	1.1952	30.31	Unlikely	1.00
Sample-5	0.9256	0.0978	0.249	36.14	0.9972	24.75	Unlikely	1.00
Sample-6	0.9303	0.0998	0.2599	1.524	1.0396	4.07	Unlikely	1.00
Sample-7	0.7831	0.0973	0.2197	68.73	0.8788	43.92	Unlikely	1.00
Sample-8	0.5986	0.0705	0.2351	4.526	0.9404	5.25	Unlikely	1.00
Sample-9	0.8235	0.0649	0.5939	1.476	2.3755	6.3	Unlikely	1.00
Sample-10	0.0889	0.1009	0.3382	2.434	1.3528	4.18	Unlikely	1.00
Sample-11	0.8659	0.0906	0.2972	11.631	1.1889	10.31	Unlikely	1.00
Sample-12	0.4289	0.0994	0.554	2.243	2.2159	6.04	Unlikely	1.00
Sample-13	0.546	0.1	0.3879	3.256	1.5517	5.58	Unlikely	1.00
Sample-14	0.6304	0.1	0.2717	2.667	1.081	4.47	Unlikely	1.00
Sample-15	0.6131	0.01	0.2532	2.316	1.0127	3.99	Unlikely	1.00
Sample-16	0.2391	0.0983	0.1957	4.414	0.7826	4.5	Unlikely	1.00
Sample-17	0.2923	0.1	0.2769	4.864	1.1077	5.43	Unlikely	1.00
Sample-18	0.6826	0.0996	0.332	2.284	1.3279	4.75	Unlikely	1.00
Sample-19	0.6301	0.0998	0.3295	2.454	1.3181	4.77	Unlikely	1.00
Sample-20	0.6722	0.1	0.232	2.75	0.9278	4.29	Unlikely	1.00
Sample-21	0.1767	0.0948	0.3517	3.822	1.4069	5.21	Unlikely	1.00
Sample-22	0.8703	0.0557	0.2123	63.047	0.8492	40.5	Unlikely	1.00
Sample-23	0.7245	0.1	0.4741	1.982	1.8963	4.66	Unlikely	1.00
Sample-24	0.9831	0.0999	0.2988	2.643	1.1953	5.09	Unlikely	1.00
Sample-25	0.8906	0.0999	0.3625	1.622	1.4501	4.83	Unlikely	1.00
Sample-26	0.6759	0.0639	0.2026	1.8683	0.8103	2.5	Not clear	-
Sample-27	0.8403	0.0999	0.2451	1.4626	1.7907	4.63	Unlikely	1.00
Sample-28	0.3645	0.0639	0.3723	1.5322	0.8968	3.6	Unlikely	1.00
Sample-29	0.7548	0.0749	0.812	0.6768	1.3678	5.46	Unlikely	1.00

Sample-30	0.6404	0.0249	9.408	0.8669	0.7469	33.12	Unlikely	1.00
Sample-31	0.6231	0.0816	0.015	4.9567	1.9069	5.79	Unlikely	1.00
Sample-32	0.2291	0.0792	0.633	2.9886	0.4737	4.74	Unlikely	1.00
Sample-33	0.4723	0.0451	0.897	10.7886	0·9425	11.01	Unlikely	1.00
Sample-34	0.6626	0.0981	0.542	3.9975	0·942	6.06	Unlikely	1.00
Sample-35	0.7322	0.0871	0.196	0.6995	0·775	2.84	Not clear	-
Sample-36	0.9722	0.0673	0.198	2.4999	0·417	3.82	Unlikely	1.00
Sample-37	0.5767	0.0341	0.879	8.1255	0·652	8.52	Unlikely	1.00
Sample-38	0.8903	0.0914	0.565	1.2499	0.1135	3.92	Unlikely	1.00
Sample-39	0.8645	0.0798	0.953	3.4158	1·435	7.78	Unlikely	1.00
Sample-40	0.9431	0.0151	0.493	7.5955	0·733	8.07	Unlikely	1.00
Sample-41	0.8756	0.0658	0.856	3.7552	0·917	8.14	Unlikely	1.00
Sample-42	0.7759	0.0557	0.4414	3.8723	1·361	6.15	Unlikely	1.00
Sample-43	0.8065	0.0661	0.5419	1.9433	1·626	5.64	Unlikely	1.00
Sample-44	0.6944	0.0999	0.693	0.9788	0·798	4.65	Unlikely	1.00
Sample-45	0.1996	0.0999	0.962	5.9934	0·352	7.5	Unlikely	1.00
Sample-46	0.9034	0.0639	0.5642	6.9983	0·253	7.49	Unlikely	1.00
Sample-47	0.9956	0.0998	0.963	1.9996	0·885	6.59	Unlikely	1.00
Sample-48	0.5303	0.0881	0.278	2.4119	1·759	4.88	Unlikely	1.00
Sample-49	0.7937	0.0558	0.588	4.5881	0·791	6.51	Unlikely	1.00
Sample-50	0.8988	0.0447	0.892	7.7483	0·993	9.73	Unlikely	1.00
Sample-51	0.8035	0.221	0.8932	1.8684	0·747	6.09	Unlikely	1.00
Sample-52	0.9889	0.0789	0.289	1.9423	0·623	3.04	Unlikely	1.00
Sample-53	0.8059	0.0429	0.4638	1.9793	0·954	4.69	Unlikely	1.00
Sample-54	0.4099	0.0539	0.4298	2.9441	2·829	6.6	Unlikely	1.00
Sample-55	0.9722	0.0658	0.7566	1.5987	0·329	5.04	Unlikely	1.00
Sample-56	0.9727	0.0746	0.4805	1.4998	0·9831	4.74	Unlikely	1.00
Sample-57	0.8754	0.0651	0.4182	0.4231	0.3842	3.16	Unlikely	1.00
Sample-58	0.5465	0.0958	0.3986	1.5146	1.7607	4.77	Unlikely	1.00
Sample-59	0.6644	0.0759	0.5273	0.6207	0.2174	3.23	Unlikely	1.00
Sample-60	0.2996	0.0881	0.4965	0.6492	0.3431	2.85	Not clear	-
Sample-61	0.7134	0.0199	0.6091	1.6982	1.1162	5.03	Unlikely	1.00
Sample-62	0.7256	0.0492	0.5804	0.7191	1.0823	4.37	Unlikely	1.00
Sample-63	0.5903	0.0331	0.3382	0.5938	0.8934	3.54	Unlikely	1.00
Sample-64	0.7837	0.0498	0.4265	0.6628	1.6681	3.48	Unlikely	1.00
Sample-65	0.3988	0.0389	0.2909	0.5687	0.8533	2.69	Not clear	-
Sample-66	0.4035	0.0758	0.4667	0.5453	0.2584	2.72	Not clear	-
Sample-67	0.4889	0.0947	0.5833	0.5847	1.0821	4.08	Unlikely	1.00
Sample-68	0.7059	0.0871	0.6833	0.5575	1.9672	5.53	Unlikely	1.00
Sample-69	0.6099	0.0584	0.7667	1.3326	1.9933	6.14	Unlikely	1.00

Sample-70	0.8702	0.0429	0.8167	0.3433	1.7727	5.78	Unlikely	1.00
Sample-71	0.1727	0.0739	0.7818	0.2322	1.2688	4.3	Unlikely	1.00
Sample-72	0.7723	0.0858	0.5179	0.1647	1.469	4.32	Unlikely	1.00
Sample-73	0.5616	0.0666	0.3977	0.639	1.513	3.98	Unlikely	1.00
Sample-74	0.4122	0.0782	0.4564	0.4327	1.194	3.56	Unlikely	1.00
Sample-75	0.9522	0.0251	0.4828	1.9934	1.262	5.23	Unlikely	1.00
Sample-76	0.8767	0.0921	0.4665	0.9983	1.606	4.93	Unlikely	1.00
Sample-77	0.0903	0.0881	0.3113	0.9996	1.838	3.7	Unlikely	1.00
Sample-78	0.3675	0.0773	0.7265	2.4119	1.9607	6.35	Unlikely	1.00
Sample-79	0.7331	0.0241	0.7464	1.5881	1.772	6.1	Unlikely	1.00
Sample-80	0.4456	0.0414	0.8364	0.7483	2.7509	6.55	Unlikely	1.00
Sample-81	0.8314	0.0698	0.3688	0.1063	1.8982	3.27	Unlikely	1.00
Sample-82	0.6031	0.0518	0.2767	0.1387	0.2279	2.02	Not clear	-
Sample-83	0.3391	0.0477	0.3685	0.9986	1.3399	4.23	Unlikely	1.00
Sample-84	0.1703	0.0239	0.3487	0.9088	1.4206	3.35	Unlikely	1.00
Sample-85	0.3016	0.0209	0.7361	2.9934	1.558	6.17	Unlikely	1.00
Sample-86	0.2172	0.0764	0.9298	5.4983	1.267	8	Unlikely	1.00
Sample-87	0.4591	0.0611	0.9872	2.7796	1.338	6.9	Unlikely	1.00
Sample-88	0.8067	0.0595	0.9984	2.011	1.7108	7.26	Unlikely	1.00
Sample-89	0.2903	0.0688	0.9999	3.5181	1.993	7.84	Unlikely	1.00
Sample-90	0.3977	0.0909	0.8337	6.7083	1.3031	8.68	Unlikely	1.00
Sample-91	0.7341	0.0767	0.1719	0.8784	0.8054	2.89	Not clear	-
Sample-92	0.4356	0.0429	0.8125	0.9423	1.4441	5.27	Unlikely	1.00
Sample-93	0.1314	0.0829	0.9996	1.6792	1.7533	6.33	Unlikely	1.00
Sample-94	0.6731	0.0646	0.9844	2.7449	0.9587	6.75	Unlikely	1.00
Sample-95	0.9991	0.0579	0.5256	1.4487	1.9871	5.87	Unlikely	1.00
Sample-96	0.4488	0.0977	0.6328	6.4098	0.9872	7.6	Unlikely	1.00
Sample-97	0.4135	0.0749	0.1875	4.3433	1.9903	5.82	Unlikely	1.00
Sample-98	0.4289	0.0179	0.0463	0.8322	0.8727	2.06	Not clear	-
Sample-99	0.6659	0.0536	0.0563	0.9647	1.6608	3.3	Unlikely	1.00
Sample-100	0.6122	0.0857	0.0778	0.6399	1.4669	2.96	Not clear	-
Sample-101	0.8662	0.0571	0.8281	1.4327	1.8513	6.56	Unlikely	1.00
Sample-102	0.7734	0.0895	0.7759	1.8938	0.7279	5.48	Unlikely	1.00
								93.00

Table 2.

Degree of Financial Distress in Sample SMEs after Multiple Loans (Group-2)

Samples	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**	**Z_n**	**Prediction**	**Score**
Sample-1	0.6233	0.0634	0.3622	1.5653	1.4489	4.42	Unlikely	1
Sample-2	0.6323	0.06125	0.362	1.364	1.4849	4.43	Unlikely	1

Sample-3	0.5115	0.0622	0.1764	1.4969	0.7056	2.89	Not clear	0
Sample-4	0.6047	0.0613	0.2345	1.4403	0.9379	3.39	Unlikely	1
Sample-5	0.669	0.0707	0.2254	2.152	0.9009	3.84	Unlikely	1
Sample-6	0.5848	0.0628	0.2042	1.524	0.8169	3.99	Unlikely	1
Sample-7	0.5324	0.0662	0.1867	1.8394	0.7469	3.19	Unlikely	1
Sample-8	0.4505	0.0531	0.2212	1.5327	0.8848	2.55	Not clear	0
Sample-9	-0.0388	0.0397	0.4545	1.367	1.8178	4.15	Unlikely	1
Sample-10	-0.2299	0.0713	0.299	2.171	1.1958	3.31	Unlikely	1
Sample-11	0.5666	0.0593	0.2431	1.3947	0.2431	2.65	Not clear	0
Sample-12	0.1016	0.0697	0.4856	2.113	1.9422	5.03	unlikely	1
Sample-13	0.4241	0.0777	0.3767	3.132	1.5067	5.25	Unlikely	1
Sample-14	0.4628	0.0734	0.2493	2.484	0.9973	3.97	Unlikely	1
Sample-15	0.3827	0.0714	0.2268	2.276	0.907	3.58	Unlikely	1
Sample-16	0.125	0.0807	0.2009	4.148	0.8036	4.22	Unlikely	1
Sample-17	-0.0118	0.0765	0.3309	2.925	1.3235	4.26	Unlikely	1
Sample-18	0.4824	0.0704	0.2933	2.169	1.1731	4.12	Unlikely	1
Sample-19	0.4548	0.0721	0.2973	2.3359	1.1893	4.21	Unlikely	1
Sample-20	0.5134	0.0764	0.2215	2.91	0.8858	4.09	Unlikely	1
Sample-21	0.1413	0.0758	0.3517	3.617	1.4066	5.01	Unlikely	1
Sample-22	0.6959	0.0446	0.2122	3.503	0.8487	4.55	Unlikely	1
Sample-23	0.4875	0.0673	0.3987	1.851	1.5949	4.7	Unlikely	1
Sample-24	0.6171	0.0627	0.2345	2.1933	0.9379	3.86	Unlikely	1
Sample-25	0.6314	0.0708	0.3213	1.5177	1.2852	4.11	Unlikely	1
Sample-26	0.525	0.0496	0.1967	1.553	0.7868	3.08	Unlikely	1
Sample-27	0.642	0.0781	0.6879	1.2056	1.8923	5.77	Unlikely	1
Sample-28	0.996	0.0891	0.2987	1.1491	1.4977	3.76	Unlikely	1
Sample-29	0.4748	0.707	0.619	1.3552	0.1216	4.54	Unlikely	1
Sample-30	0.3822	0.226	1.588	1.7623	1.3917	8.46	Unlikely	1
Sample-31	0.4839	0.0159	0.013	1.8433	1.6768	3.43	Unlikely	1
Sample-32	0.0299	0.0267	0.459	1.9988	1.8669	4.65	Unlikely	1
Sample-33	0.2995	0.0344	0.439	1.6934	0.4967	3.37	Unlikely	1
Sample-34	0.5027	0.0469	0.247	1.3983	0.3886	2.71	Not clear	0
Sample-35	0.4802	0.0558	0.117	1.9996	0.6975	2.94	Not clear	0
Sample-36	0.6826	0.0454	0.126	1.5219	0.7995	3.01	Unlikely	1
Sample-37	0.1887	0.0189	0.879	1.6881	0.9339	5.1	Unlikely	1
Sample-38	0.5884	0.0225	0.262	1.8483	0.1035	2.81	Not clear	0
Sample-39	0.4088	0.0257	0.754	1.5684	1·435	5.39	Unlikely	1
Sample-40	0.6499	0.0699	0.441	1.5623	0·439	3.71	Unlikely	1
Sample-41	0.5188	0.0236	0.723	1.7993	0·733	4.85	Unlikely	1
Sample-42	0.3758	0.0197	0.2113	1.7941	1·055	3.31	Unlikely	1

Sample-43	0.4469	0.0227	0.4598	1.6977	0·934	4.04	Unlikely	1
Sample-44	0.5544	0.0315	0.407	1.6498	0·642	3.68	Unlikely	1
Sample-45	0.1699	0.0432	0.764	1.4567	0·299	3.96	Unlikely	1
Sample-46	0.4639	0.0345	0.2648	1.7887	0·115	2.67	Not clear	0
Sample-47	0.3058	0.0255	0.4566	1.7806	0·409	3.39	Unlikely	1
Sample-48	0.1394	0.0598	0.1179	1.0975	1·285	2.58	Not clear	0
Sample-49	0.6639	0.0172	0.376	1.6995	0·567	3.64	Unlikely	1
Sample-50	0.6282	0.0174	0.6722	2.0991	0·455	4.71	Unlikely	1
Sample-51	0.7139	0.1629	0.7762	3.0255	0·747	6.21	Unlikely	1
Sample-52	0.1982	1665	0.105	1.2799	0·146	1.13	very high	0
Sample-53	0.4356	0.0226	0.413	3.348	0·495	4.43	Unlikely	1
Sample-54	0.2397	0.0459	0.3298	4.5955	1·623	5.82	Unlikely	1
Sample-55	0.7029	0.0275	0.3045	1.6768	0·124	3.02	unlikely	1
Sample-56	0.4729	0.0159	0.3815	2.5669	0·5738	3.96	unlikely	1
Sample-57	0.6758	0.0595	0.2941	0.3135	0.1647	2.03	Not clear	0
Sample-58	0.4462	0.0839	0.4853	1.5068	0.3433	3.5	Unlikely	1
Sample-59	0.3643	0.0378	0.1795	0.5705	0.1487	1.57	very high	0
Sample-60	0.1998	0.0693	0.1566	0.4429	0.0772	0.98	very high	0
Sample-61	0.5636	0.0181	0.6728	1.1927	0.2246	3.86	Unlikely	1
Sample-62	0.6559	0.0359	0.884	0.4196	0.9274	2.31	Not clear	0
Sample-63	0.3919	0.0265	0.4766	0.4459	0.3274	2.68	Not clear	0
Sample-64	0.6848	0.0279	5.389	0.4257	0.9685	19.87	Unlikely	1
Sample-65	0.2808	0.0688	6.515	0.5687	0.817	23.09	Unlikely	1
Sample-66	0.3455	0.0765	0.1536	0.3429	0.1639	1.4	very high	0
Sample-67	0.3987	0.0832	0.8544	0.3893	0.0589	3.71	Unlikely	1
Sample-68	0.4754	0.0795	0.6495	0.4566	0.2745	3.37	Unlikely	1
Sample-69	0.5294	0.0306	0.5759	1.1318	0.3566	3.61	Unlikely	1
Sample-70	0.7762	0.0314	0.5537	0.2759	0.9818	3.95	Unlikely	1
Sample-71	0.1669	0.0335	0.7696	0.1377	0.8756	3.75	Unlikely	1
Sample-72	0.6674	0.0534	0.5971	0.1488	0.7549	3.69	Unlikely	1
Sample-73	0.4786	0.0497	0.7887	0.484	0.6974	4.23	Unlikely	1
Sample-74	0.4074	0.0419	0.9775	0.3497	0.6729	4.66	Unlikely	1
Sample-75	0.7578	0.0155	0.8452	1.5988	0.9447	5.62	Unlikely	1
Sample-76	0.5884	0.0624	0.9745	0.5676	0.7843	5.13	Unlikely	1
Sample-77	0.0752	0.0456	0.9253	0.6785	0.6974	4.31	Unlikely	1
Sample-78	0.2479	0.0354	0.6983	1.4918	1.547	5.09	Unlikely	1
Sample-79	0.3936	0.0194	0.5995	0.889	1.462	4.47	Unlikely	1
Sample-80	0.4152	0.327	0.7818	0.6478	0.9763	4.9	Unlikely	1
Sample-81	0.5718	0.0506	0.1824	0.102	0.9372	2.36	Not clear	0
Sample-82	0.5438	0.0504	1.514	0.109	0.1626	5.95	Unlikely	1

Sample-83	0.2457	0.0124	0.1463	0.5769	0.9566	2.09	Not clear	0
Sample-84	0.1425	0.0196	0.2486	0.3744	1.1447	2.39	Not clear	0
Sample-85	0.1889	0.0169	0.6368	0.7793	1.3436	4.16	Unlikely	1
Sample-86	0.1731	0.0645	0.7295	3.4725	0.1581	4.95	Unlikely	1
Sample-87	0.1676	0.0534	0.8877	1.1152	0.6774	4.55	Unlikely	1
Sample-88	0.1557	0.0267	0.8986	1.9934	0.7249	5.11	Unlikely	1
Sample-89	0.1497	0.0487	0.6976	1.9775	0.9674	4.7	Unlikely	1
Sample-90	0.1397	0.0712	0.4332	2.1542	0.7279	3.72	Unlikely	1
Sample-91	0.1286	0.0676	0.1415	0.7299	0.4685	1.62	very high	0
Sample-92	0.1535	0.0124	0.5128	0.3983	0.8167	2.95	Not clear	0
Sample-93	0.0627	0.0627	0.6998	0.7776	0.6639	3.6	Unlikely	1
Sample-94	0.1792	0.0448	0.6849	1.519	0.5589	4.01	Unlikely	1
Sample-95	0.889	0.0275	0.2254	0.6786	1.2745	3.53	Unlikely	1
Sample-96	0.393	0.0676	0.4325	4.349	0.3586	4.96	Unlikely	1
Sample-97	0.376	0.0641	0.1068	1.321	0.9018	2.59	Not clear	0
Sample-98	0.1596	0.0145	0.0368	0.9086	0.678756	1.56	very high	0
Sample-99	0.607	0.0338	0.0269	0.5959	0.6549	1.88	very high	0
Sample-100	0.537	0.0658	0.0701	0.2755	0.7984	1.93	very high	0
Sample-101	0.659	0.0378	0.5276	0.4349	0.8519	3.69	Unlikely	1
Sample-102	0.567	0.0494	0.5752	1.7519	0.2277	3.93	Unlikely	1
								78