# Measuring Credit Risks for Sustainable Lending of SMEs towards achievement of MDGs in Rwanda

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# *Introduction and motivation*

- Credit risk refers to the risk of default by borrowers which arises from the uncertainty over the cash flow from the borrower's project (Morris and Shin, 2009).
- Traditionally, the terms of the loan have been linked to the borrower's cash flow,
- This results to SMEs being deemed as a risky venture due to the low level of cash flow.
- Financiers ignore other factors that could mitigate for credit riskiness such as management style and innovation

- Arora et. al, (2001) argues that financial institutions do not consider the experimentation and innovation propensity evident in small firms in their financing decisions for SMEs.
- The problem has become a lemons market problem where financiers are not able to accurately separate the firms into those which have a higher probability to default and those that have a lower probability to default due to information asymmetry. It is likely that SMEs that are more innovative and forward looking are less likely to default.
- In Rwanda the SME sector comprising 98% of the businesses in Rwanda and 41% of all private sector employment (Ministry of Trade and Industry, 2010).
- The Ministry recognizes the potential of SME sector in reducing Rwanda's trade deficits and creating employment.
- But they face the common problem of poor access to financing

- Linking this to MDGs UNIDO (nd) sees the widening gap between rich and poor worldwide as a major threat to global security and economic integration where which is mainly do lack of opportunities that exist for the poor to help themselves.
- The development of SMEs is one of the key avenues through which to achieve poverty reduction
- Lack of linkages among small businesses and support institutions often prevents SMEs from realizing their full growth potential particularly in the context of global value chains.
- Rwanda has made remarkable strides towards poverty eradication as it strives to achieve the millennium development goals by 2015. One of the avenues that has been used is the SMEs Development Policy of 2010 through which the country hopes to attain the middle level income status by growing the SMEs sector which accounts for 98% of all business enterprises in Rwanda

- It is therefore imperative to assess the whole issue of credit worthinessness of SMEs and how it is viewed in Rwanda by the financial institutions.
- The objectives of this study are twofold:
  - First is to examine both the ex-post and ex-ante determinants of loan amounts for the selected SMEs and
  - second is to estimate the ex post and ex ante probability to default for SMEs in Rwanda using both financial and non-financial information.

# Gaps in Literature

- Altman (1068) in his pioneering work used accounting-based credit risk modeling and modeled credit risk as a linear combination of explanatory variables comprising several financial ratios using discriminant analysis.
- Together with many other authors who used accounting information to predict business failure (e.g. Martin 1977; and Zmijewski 1984). Bonfim (2007) they find that both firm specific variables such as financial structure, profitability and liquidity as well as macroeconomic variables all contribute to credit riskiness of firms
- Several studies have recognized the role of non-financial factors in predicting financial distress of firms (e.g. Zavgren (1985), Becchetti and Sierra (2003) and Keasey and Watson, 1987)
- Other studies eg. Psillaki et. al. (nd) suggest that a combination of financial and non-financial factors should enhance a bank's ability to predict business failures more accurately than a model that relies solely on the use of financial indicators.
- Blanco et. al. (nd) find that non-financial firm specific characteristics make a significant contribution to increasing the default prediction power of risk models built specifically for SMEs.

# Credit Scoring

- According to Covaros (2010) credit-scoring technology is widely used by banks as a method to diminish the asymmetric information gap between the borrower and lender, which leads to a more efficient allocation of capital. He distinguishes between two perspectives of credit scoring. A personal credit score also known as a FICO score or Beacon score which measures an individual's personal consumer credit history (such as whether he or she has paid their bills on time and the amount of debt on their credit cards) An in-house credit scoring model which use a personal credit score combined with other variables such as management experience or the business's cash-flow.
- This statistical model identifies significant variables, applies relative weights to each, and provides an in-house "score." In this study the FICO score is considered as the ex-post or backward looking credit risk assessment while the in-house credit-scoring is considered as the ex-ante or forward looking approach. The use of personal credit scoring such as FICO and Beacon Scores is often seen to discriminate against small and rural borrowers. Cowen et. al (2000) argue that most rural banks use relationship lending other than credit score lending

# Contribution

- The challenge remains on how to separate the ex-post and ex-ante credit risk of SMEs and if there are certain visible characteristics that would signal a more certain future for SMEs. Taking such an approach, some SMEs that would be categorized as having a high probability of default given their current situation and therefore denied access to finance would probably have a more certain future and therefore be more profitable to finance than those that appear to be healthy today.
- This paper attempts to establish whether there is any difference between ex-post and ex-ante credit risk and the impact it has on the probability to default. It is possible to assess both the ex post credit risk by looking at the previous performance and ex ante credit risk by looking at the future prospects of the firms

# Methodology

- Following Covaros (2010) this paper adopts the statistical in-house credit-scoring model.
- The study by Covaros (2010), using small business loan portfolio data from a national Community Development Financial Institution (CDFI), develops an in house credit –scoring model, which help CDFIs quantify their risk, which often allows them to extend more credit in the small business community.
- The study suggests four categories of predictive indicators of loan default for CDFI SBL First is the borrower-specific characteristics such as corporate structure, FICO score, education and industry; second is the loan-specific characteristics such as guarantee percentage, loan amount, and interest rate; third is the lender- specific characteristics such as loan-officer identity, loan officer type, and region and fourth is the macroeconomic variables such as changes in the business cycle and in local unemployment.

# Methodology (cont)

- The current study will only consider the borrower specific characteristics taking all other characteristics as given. This is reasonable because the all the SMEs are operating in a similar macroeconomic environments and are borrowing from the same financial institution.
- The borrower specific characteristics will be divided into two following Vermeulen (2008) who separated firm specific characteristics into both financial and non-financial. In this study selected profitability, liquidity and leverage financial ratios will be used as a backward looking measure of SMEs' wellness while non-financial indicators will include innovation and managerial efficiency which are considered as forward looking measure of SMEs' wellness.
- A subjective measure of Innovation is used where some sectors are thought to be more innovative than others. Managerial efficiency will be measured following Morten et al. (2007) who found that firms that are managed by family CEOs are more likely to fail compared to those that are headed by nonfamily CEOs. Therefore, managerial efficiency will be a binary variable with a value of 1 where the company is a family firm and 0 otherwise.

# Model Specification

- The probability to default is modeled as a logistic model specified as follows

  $PD_i(X_i, Z_i) = 1/1 + e^{\beta Xi + \gamma Zi}$............................................................................. (i)

- Where $X_i$ represent the backward looking financial information and $Z_i$ represents the forward looking financial information. B and γ are parameters of the model.

- Rewriting equation (i) as a logistic transformation yields

- $\ln (PD_i/1\text{-}PD_i) = \beta X_i + \gamma Z_i$............................................................................(ii)

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- Three backward looking financial ratios will be used in this study namely Return on Assets (ROA), current Assets (CA), Total Assets (TA) and Profit Before Interest and Taxes (PBIT).. The forward looking non-financial measures used in this study are innovation (IN) and managerial efficiency (TE). The age (AGE) of the firm will also be included as a variable

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- Equation (ii) can therefore be rewritten as

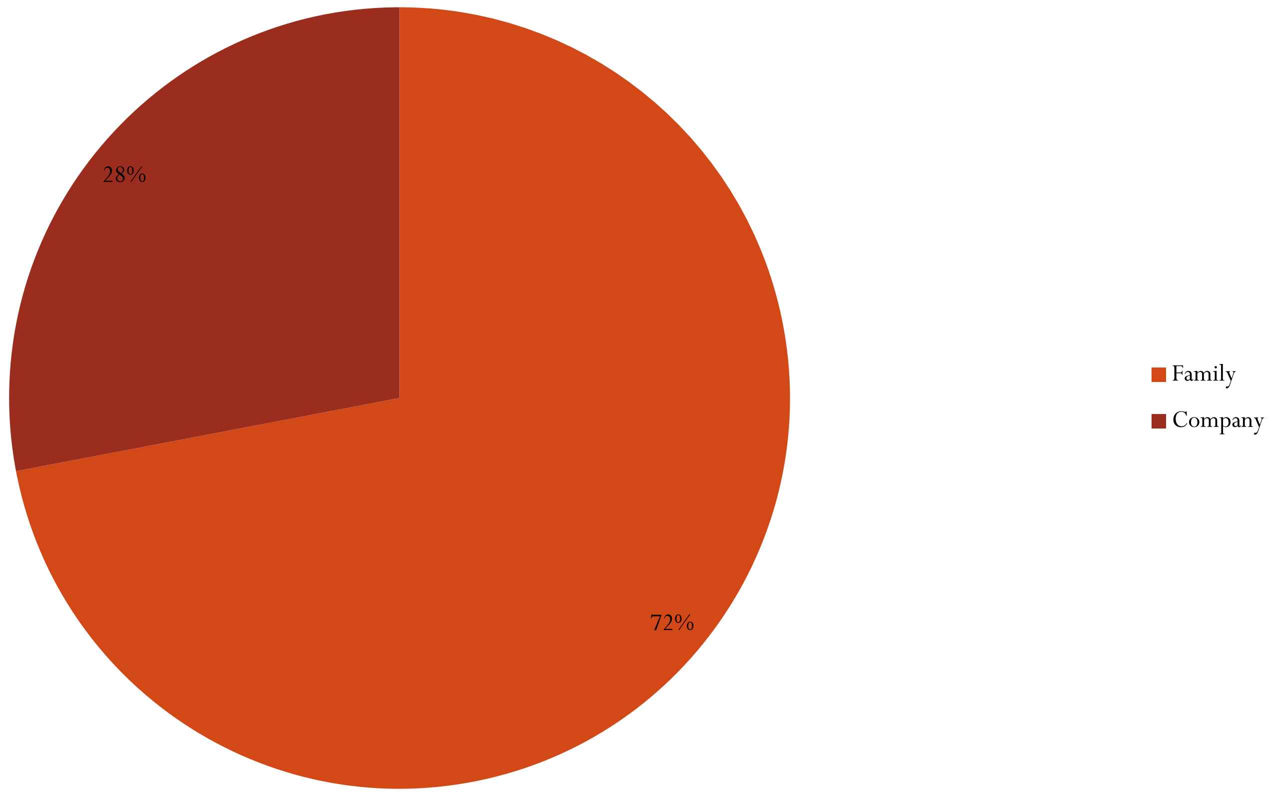
  $\ln (PD_i/1\text{-}PD_i) = \beta_0 + \beta_1 ROA + \beta_2 CA + \beta_3 DA + \gamma_1 IN + \gamma_2 ME + \gamma_3 AGE + \varepsilon_i$...........(iii)

# Data and Variables

- This study uses both financial and non-financial borrower specific data for a sample of 50 SMEs in Rwanda. In order to control for macroeconomic variables such as interest rates all the SMEs borrow money from one institution Fina Bank such that they face similar macroeconomic conditions,
- The data captures financial variables such as current assets and liabilities, total assets and profit before interest and tax (PBIT)
- For the non-financial borrower specific variables the data captures the type of business which are divided into four groups based on sectors that are deemed to be most innovative. Operations that are deemed to be more business focused are classified as most innovative while those that are deemed to be least business oriented are classified as least innovative based on the researcher's judgment.
- Another characteristic found to be important is the type of business ownership which is divided into either family or company ownership.
- The number of years in operation, amount of loan advanced and the repayment period is also captured.
- Since financial information has been traditionally used to determine credit worthiness of borrowers, the probability to default is determined by the completeness of this information.
- While all the firms in the sample have information on the total and current assets as well as PBIT, some of them do not have information on the current liabilities.
- A firm with no current liability information is deemed to have a higher probability to default (1) while the firm that has information on current liability takes 0 probability.

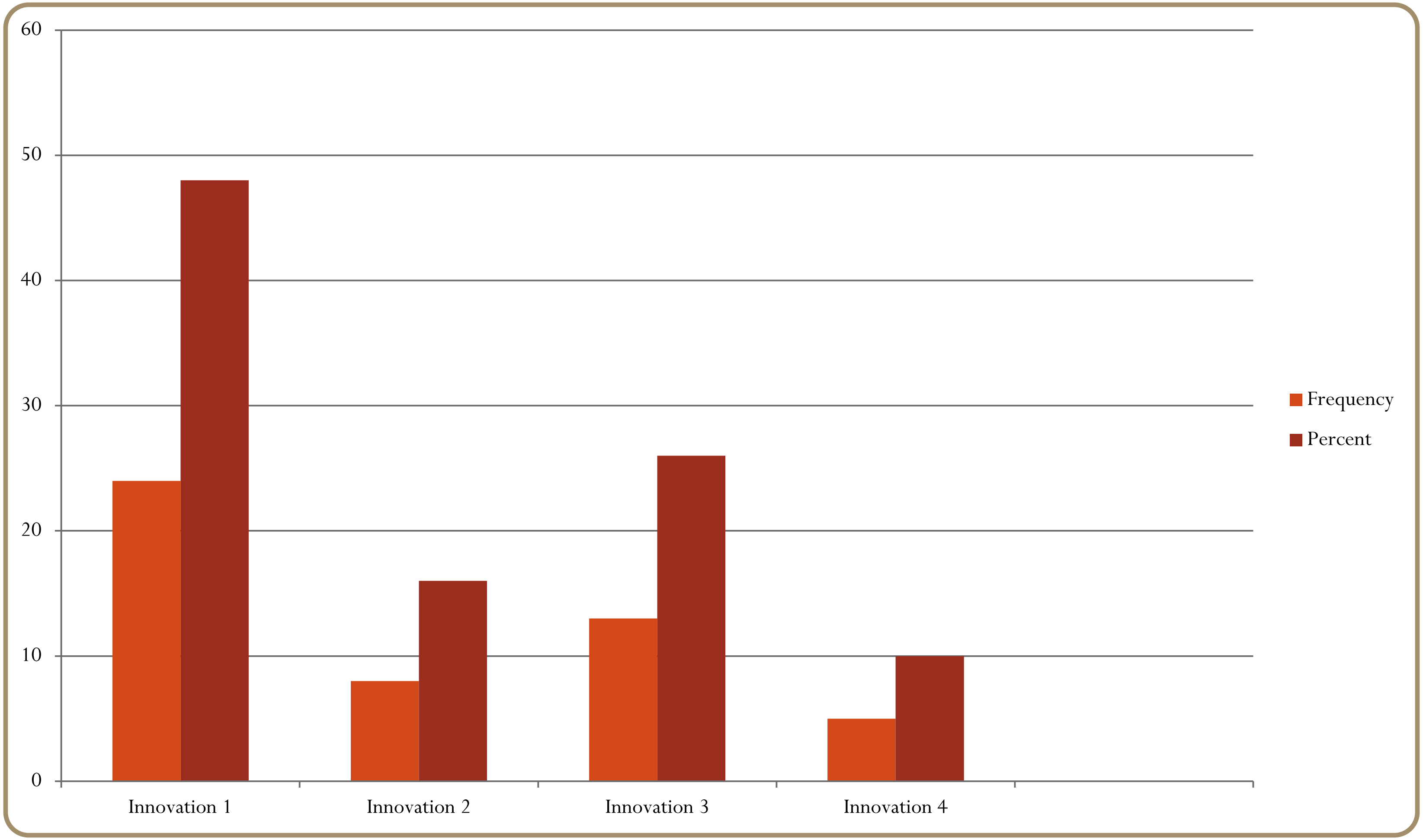
# Descriptive Analysis

- **Business Ownership**
- Business ownership is considered to be paramount in this study given that managerial efficiency is reflected in the ownership.
- As shown in figure 1, 72% of the SMEs considered are family owned while 28% of them are company owned.


28%
72%
Family
Company

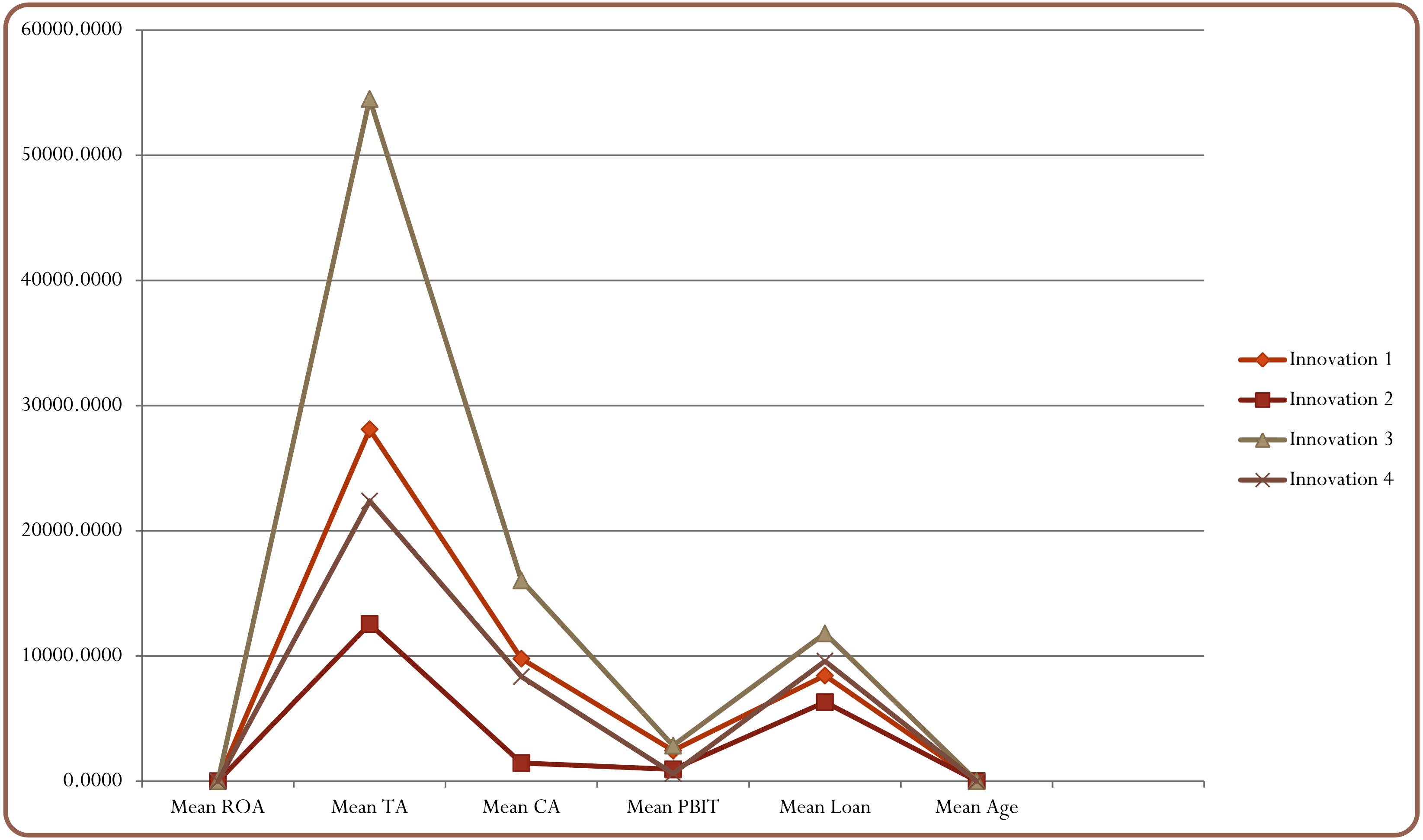
# Descriptives (Cont)

- **Business type and Innovation**
- In the sample, 11 business types are captured. The business types are then categorized into four level of innovation using subjective judgment based on which has a bigger probability of product differentiation and value addition.
- The first one which is the most common are called "commerce" are thought to be the most business focused businesses and considered as most innovative (Innovation 1).
- The second category is transport considered as Innovation 2; followed by Innovation 3 comprising of agriculture, hospitality, foodstuff and carpentry) and the final category, Innovation 4 comprise of boutique, building fittings, stationery, hardware and bakery.
- According to Figure 2, most of the businesses that get loans are categorized as innovative which implies that they have a higher chance of growth and hence more potential to pay.


60
50
40
30
20
10
0
Innovation 1
Innovation 2
Innovation 3
Innovation 4
Frequency
Percent

# Descriptives (Cont)

- **Financial and Non-Financial Characteristics**
- In order to establish how the level of innovation assumed interacts with the financing decisions, Figure 3 presents the relationship of different financial and non-financial characteristics for different type of businesses
- Examining the figure, total assets seem to be the most determining factor for financing decisions since the businesses with the highest level of Total Asset also have the highest amount of loans.



60000.0000
50000.0000
40000.0000
30000.0000
20000.0000
10000.0000
0.0000
Mean ROA
Mean TA
Mean CA
Mean PBIT
Mean Loan
Mean Age
Innovation 1
Innovation 2
Innovation 3
Innovation 4

# Determinants of Loan Amount

- In order to capture the role of both forward looking and backward looking variables used by the banks to determine the amount of loans to be advanced to the SMEs, an OLS model is used
- The first OLS model regresses the loan amounts against the financial variables namely Current Assets, Total Assets and PBIT. The results are presented in Table 1

# Table 1

| Variable | Coeeficient | Standard Error | t-statistic | P-Value |
|---|---|---|---|---|
| **Current Assets** | 0.246 | 0.0525 | 4.69 | 0.000 |
| **Total Assets** | 0.03 | 0.0236 | 1.13 | 0.265 |
| **PBIT** | 0.18 | 0.389 | 0.46 | 0.650 |
| **Constant** | 5450.565 | 789.901 | 6.90 | 0.000 |
| **R-squared** | 0.679 | | | |
| **Adj R-squared** | 0.658 | | | |

# Discussion

- From the results presented in Table 1, all the three financial variables are positively related to the loan amount. However, only the Current Assets show a significant relationship. This implies that the most significant determinant for loans is current assets
- Given that both TA and PBIT are not significant, it is necessary to include ROA in the model since in financial management literature, ratios are more informative than individual financial measures. Table 2 presents the OLS results including ROA

# Table 2

| Variable | Coeeficient | Standard Error | t-statistic | P-Value |
|---|---|---|---|---|
| **Current Assets** | 0.238 | 0.053 | 4.500 | 0.000 |
| **Total Assets** | 0.017 | 0.025 | 0.660 | 0.514 |
| **PBIT** | 0.432 | 0.454 | 0.950 | 0.346 |
| **ROA** | -13358.720 | 12315.420 | -1.080 | 0.284 |
| **Constant** | 6343.425 | 1139.757 | 5.570 | 0.000 |
| **R-squared** | 0.688 | | | |
| **Adj R-squared** | 0.659 | | | |

# Discussion

- Results in Table 2 show that ROA is not a significant determinant of loans giving only current asset as significant
- The next OLS model examines the non-financial determinants of loans the results of which are shown in Table 3

# Table 3

| Variable | Coeeficient | Standard Error | t-statistic | P-Value |
|---|---|---|---|---|
| **Current Assets** | 0.190 | 0.061 | 3.13 | 0.003 |
| **Total Assets** | 0.015 | 0.027 | 0.54 | 0.59 |
| **PBIT** | 1.135 | 0.606 | 1.87 | 0.068 |
| **ROA** | -14239.540 | 13075.440 | -1.09 | 0.283 |
| **Business Age** | -25.894 | 168.848 | 1.58 | 0.879 |
| **Ownership** | 3505.225 | 2218.977 | -1.01 | 0.122 |
| **Innovation 1** | -2356.642 | 2333.297 | -0.78 | 0.319 |
| **Innovation 2** | -1999.238 | 2570.465 | -0.17 | 0.441 |
| **Innovation 3** | -422.496 | 2421.068 | 1.93 | 0.862 |
| **Constant** | 4752.405 | 2457.021 | 3.13 | 0.06 |
| **R-squared** | 0.7177 | | | |
| **Adj R-squared** | 0.6526 | | | |

# Discussion

- From the results in Table 3, once other borrower specific variables are considered, PBIT is now significant in explaining the variations in the loan amount as well as the current assets.
- Ownership is also a significant factor but contrary to expectations family owned businesses seem to be considered more credit worthy than those owned by companies.
- This may be reflective of relationship lending suggested by Cowen et. al (2000). Innovation is seen to have a negative relationship with loan amount and is not even significant . This is not surprising given that it is a subjective measure. Business age is not significant in the model.

# Predicting the Probability to Default

- A logistic regression model is used to predict the Probability to Default (PD) using both foreward Looking and Backward looking variables.
- The first model considers only financial variables and the results are presented in Table 4

# Table 4

| Variable | Coeeficient | Standard Error | z-statistic | P-Value |
|---|---|---|---|---|
| **Current Assets** | 0.0000336 | 0.0000327 | 1.03 | 0.305 |
| **Total Assets** | 0.0000166 | 0.0000127 | 1.3 | 0.192 |
| **PBIT** | -0.0006785 | 0.0002951 | -2.3 | 0.021 |
| **ROA** | 28.42734 | 16.58709 | 1.71 | 0.087 |
| **Constant** | 0.2019843 | 0.9995141 | 0.2 | 0.84 |

# Discussion

- The result show that Current Assets, PBIT and ROA are all significant predictors of Probability to Default with both CA and ROA increasing the probability to default and PBIT reducing the probability to Default.
- This is not surprising given that ROA is a ratio of PBIT and TA which would imply that the firms do not inject profits back into business in order to increase the assets.

# Discussion

- Given that most of the sampled businesses are family owned it is possible that profits are used for personal use other than business advancement which is not good for lenders
- Table 5 combines both Backward looking and Forward Looking variables to predict the probability to default
- The results show that PBIT and ROA are the most significant predictors for the probability to default as well as innovation. The signs are just as in the previous model with the PBIT reducing the odds and ROA increasing the odds. Innovation reduces the probability to default while business age is not significant in the model.

# Table 5

| Variable | Coeeficient | Standard Error | z-statistic | P-Value |
|---|---|---|---|---|
| **Current Assets** | 0.00013 | 0.00009 | 1.42 | 0.155 |
| **Total Assets** | 0.00005 | 0.00005 | 0.91 | 0.363 |
| **PBIT** | -0.00131 | 0.00076 | -1.73 | 0.083 |
| **ROA** | 97.90185 | 30.68210 | 3.19 | 0.001 |
| **Business Age** | -0.18232 | 0.12377 | -1.47 | 0.141 |
| **Ownership** | 2.19067 | 2.24025 | 0.98 | 0.328 |
| **Innovation 1** | -3.18304 | 1.64868 | -1.93 | 0.054 |
| **Innovation 2** | -0.11790 | 1.85666 | -0.06 | 0.949 |
| **Constant** | -3.40568 | 2.45900 | -1.38 | 0.166 |

# Conclusion

- The analysis show that PBIT and ROA is the most significant predictors of the Probability to Default. It is further revealed that when business ownership is considered there is no advantage of company ownership over the family ownership. Firm age is not significant in determining the probability to default. Probability to default is seen to decrease with a increase in Profit (PBIT). Probability to Default is positively related to ROA.
- From the analysis it is clear that differentiating SMEs using non-financial characteristics such as innovation and ownership is likely to improve on the default rate which now stands at 12.5% according to FINA Bank records