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MODELLING SUCCESS IN COMMERCIALISATION: USING A SAMPLE OF AFRICAN MICROFINANCE INSTITUTIONS

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Abstract

Commercial capitalists seek opportunities in profitable and liquid microfinance institutions (MFIs) and emerging markets with promising growth prospects. Adequate disclosure of financial performance attracts commercial lenders to develop long-term financing relationships with microfinance institutions in Africa. This study examines both the process and the dynamics of commercial microfinance from the perspectives of commercial lenders' interests, and it measures the probability of success in tapping the financial markets. A commercialisation success model is developed for tapping commercial funds and to assess its suitability in predicting success with a cross-country sample of MFIs from 21 African countries over the period 1998 - 2003. The predication model aims to minimise chances of failure, act as a screening system by investors as well as a self-assessment tool for MFIs intending to seek commercial capital. The findings of the study suggest how MFIs can break free from 'captive' donor funding as a necessary platform for the switch to commercial finance in the industry.

Keywords: Logistic models; attraction factors; commercial index, predictors of success; commercial microfinance; Africa

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Note: This paper is based on part of the author's PhD dissertation at the University of Stellenbosch Business School.

INTRODUCTION

It is generally agreed that microfinance is pro-poor and that its role as a policy tool for effective and sustainable poverty reduction is undeniable (Beck & Fuchs, 2004; Stern, 2001; Beck, Dermirguc-Kunt & Levine, 2004; ADB, 2000; Klasen, 2005). Poverty alleviation strategies and the achievement of millennium development goals (MDGs) in many developing countries in Africa are clearly dependent on the success of microfinance as a business model and other market-based approaches. The rationale behind this argument is that microfinance assures improved access and efficient provision of financial products and the development of assets.

The lack of access to continued funding is the greatest threat to small institutions in developing countries. While donations have made an enormous contribution to microfinance development, attempts to scale up funding from this traditional source have been an uphill task. It is argued that non-official ODA in microfinance is no longer able to meet the huge funding gap, now estimated at US$300 billion (Meehan, 2004). This presents a huge demand and a big challenge to encourage the flow of private capital into the sector. Therefore microfinance institutions (MFIs) need an alternative and a clear financial planning strategy in order to remain relevant in reaching a significant population of the poor with financial services.

There is a direct relationship between growth of an organisation and the need for external financing. The higher the rate of asset growth the greater the need for external financing, other things being equal (Upneja & Dalbor, 2001; Zalpalska et al., 2007; Vasiliou & Karkazis, 2002). McKee (2001b) and Charitonenko et al. (2004) note that financing growth with commercial debt (in this paper referred to as commercialisation) has become more common in mature microfinance markets, such as Indonesia, Latin America, Bosnia, Uganda, Morocco, Ghana and Sri Lanka. Indeed commercial players are major forces in the microfinance market in a number of countries. Citing the Indonesian experience, Charitonenko et al. (2004) state that commercialisation has a positive impact on 'breath' of outreach: "Indonesia as the world's leader in terms of the percentage of microcredit supplied on a commercial basis, has an estimated debt of more than 80 per cent of the industry total funding".

The microfinance sector is increasingly responding to financial market interests and investor demand. For example, a first rated (securitised obligation loan named BOLD 2007), but second issue in the capital market placed by Morgan Stanley attracted 21 investors (Arvelo et al., 2008). Recent studies (Daley-Harris, 2009; CGAP, 2007; Cull et al., 2008; Arvelo et al., 2008; Meehan, 2004; Charitonenko et al., 2004; De Souza et al., 2004) show an increasing interest by the commercial markets in financing microfinance. It is also evident that donors do not have sufficient resources to inject into the sector due to the huge demand and supply gap – hence the proposal for integration of MFIs to the larger financial system for sustained funding

(CGAP, 2002a; Arch, 2005). What is yet to be shown, however, is whether microfinance can become an integrated part of the formal financial system?

This paper therefore addresses the central question of how MFIs can access commercial capital and become part of the larger financial system. The study examines the strategy of commercialisation in general and in particular seeks to contribute to the debate by availing evidence based on African MFIs' experience as well as the extent of integration of MFI financing to the financial markets. It develops the pathway through which an MFI can become part of the financial landscape and investigates the factors that underpin success in commercialising microfinance institutions.

The paper incorporates the experience of African MFIs over three years to develop and examine a success model for tapping private capital. The estimated model informs and guides MFIs and commercial lenders of ways they can establish financing connectivity with each other. The study focuses on firm level performance factors that is said to influence commercial capital (and a reflection on other variables). In doing so, this paper builds on a foundation towards defining critical success strategies for tapping commercial capital.

The findings of this paper add to the understanding of the financing relationship between commercial lenders and MFIs, offer evidence that a lack of clarity and scarcity of information on performance is a key deterrent to private investors and it provides insight into factors associated with the successful commercialisation of microfinance in Africa. The impact of commercial microfinance on long-term social value of microfinance indicates that size and social variables plays a minimal role in differentiating which institutions attract commercial capital. The results indicate the emergence of new finance sources, widened financing options for regulated MFIs and the capacity to relax growth constraint in the industry

RELEVANT LITERATURE AND COMMERCIALIZATION VIEW

The appropriate method of financing microfinance institutions has been a fundamental issue of concern. Proponents of poverty-focused microfinance (Charitonenko, 2003) are of the view that microfinance, as a social product, should not be offered on a for-profit basis. This argument created the unique precedence where funding continued to come from donor sources, hence the name donor industry. According to this school of thought, MFIs require loan capital that is not charged on a commercial basis and further argues that embracing commercial practices would hurt their core clients. Hence opponents of commercialisation associate the term to mean changing the course of microfinance, while those in favour of commercial capital intervention argue that this is simply a perception problem.

Commercial capital intervention may be unstoppable as it is seen as the way out of the financing constraints facing the sector. New commercial sources for microfinance development are needed for continued existence and furtherance of the vision of microfinance. This paper underscores the need to explore and experiment new funding sources and an exit strategy, away from captive donor funding that has characterised the industry.

Proponents of commercialisation argue that since traditional donor funding sources of microfinance are unavailable, MFIs should seek for alternative finance sources to scale-up current outreach to the poor (Cull et al., 2008; Lewis, 2008). Microfinance has witnessed high rate of asset growth in its portfolio and the higher the growth the greater the need for external financing, other things being equal (Upneja & Dalbor, 2001; Zalpalska et al., 2007; Vasiliou & Karkazis, 2002). Finance experts argue that any significant growth in portfolio investment must be met with increased sources of finance (Berger, Herring & Szego, 1995; Helwege & Liang, 1996; Berger & Udell, 2001).

McKee (2001b) and Charitonenko et al. (2004) note that financing growth with commercial debt has become more common in mature microfinance markets, such as Indonesia, Latin America, Bosnia, Uganda, Morocco, Ghana and Sri Lanka. Indeed commercial players are major forces in the microfinance market in a number of countries. In support of commercial microfinance, Sukarno (in CGAP, 2001) said commercialisation of microfinance is becoming the order of the day after achieving sustainability, while Christen (2000) in his study of breakthrough MFIs concluded that, "frontier MFIs tend to use commercial approaches to microfinance". Donors do not have sufficient resources to inject into the sector due to the huge demand and supply gap – hence the proposal for integration of MFIs to the larger financial system for sustained funding (CGAP, 2002a; Arch, 2005). This baseline argument points to the fact that the traditional view of microfinance funding is changing, with increased positive trials of commercial microfinance.

Commercialisation in the context of attracting commercial capital is an alternative funding strategy as opposed to waiting on donations, however, what is yet to be shown, is whether microfinance can become an integrated part of the formal financial system. Although commercial lenders are willing to increase funding to the microfinance sector, to many the decision to finance an MFI is a high risk undertaking (Koveos & Randhawa, 2004). This perception problem poses the challenge of access to commercial capital for a number of MFIs, particularly from Africa. Investors state some of the barriers for increasing the flow of private capital as lack of convincing profitability, weak institutions, and small size of the institutions (Cull et al., 2008; Arch, 2005). For other institutions, there is the fear of risk of financial leverage that comes with high interest debt (Berger et al., 1995).

It is acknowledged that microfinance institutions have difficulties going to the financial markets (Cull et al., 2008; Arch, 2005). This is an emerging industry in many parts of the world and as such, many MFIs fail to meet the conditions while some of the criteria imposed by commercial lenders are not clear to the institutions. This study therefore seeks to provide evidence on the influence of hypothesised variables on commercial financing decisions of African MFIs. It also suggests key driving forces behind commercial capital flows.

RESEARCH METHODS

Cross-country data of 103 African MFIs was sampled from the MIX MARKET ™ web-based microfinance information database. MIX MARKET ™ is the world's largest microfinance database containing outreach and impact data, financial data, audited financial statements in addition to country relevant macro-economic and social development indicators. At the time of this study, the database provided world-wide data on 435 MFIs, 68 investors and 112 partners. The following section provides the description of the sample and the type of data collected.

Data collection: sample description

The survey looked at all the 50 countries in the African continent and segmented the continent into four regions. The number of countries investigated in each region was as follows: North and Sahara region, 12; West Africa, 12; East and Central, 15; and Southern region, 11. The survey then selected countries within the regions that have microfinance programmes for identification of microfinance institutions. The sampling frame consisted of the total population of African MFIs posting data in the MIX database between 1998 to the end of the calendar year 2003. This population constituted 188 African firms. Following Ozkan (2001), Peyer and Shivdasani (2001), Hendricks and Singhal (2001), and Laittinen (2002) the sampling criterion for firm inclusion in the model was defined as those MFIs with consecutive three-year financial data between 1998 and 2003. This definition resulted in a final sample of 103 MFIs and 309 observations after dropping firms with missing observations or those with non-continuous data series (Hasan, Wang & Zhou, 2009). This represented 55 per cent of total population of all 188 Africa firms drawn from 21 countries. The 21 countries were spread in the regions as follows: North and Sahara, 4 countries; West Africa, 7 countries; East and Central Africa, 6 and Southern Africa region, 4 countries. In general, effective sample show West African countries have more visibility in the MIX database. The section that follows describes how the measures of success were obtained.

Modeling success in commercialisation: conceptualisation of the dependent variables

The measure of success in commercialisation was one of the challenges of this study. It was important though to establish whether it is possible to develop a uniform commercial success prediction rule for MFIs in Africa This study explored two levels of the likelihood of success in commercialisation:

*(a) Level **I** success of measure: leverage multiplier added*

Success was measured in two levels, level (I) by a single cardinal measure for gauging the probability of success in tapping commercial markets. This measure was defined as the equity multiplier (**EM**), which is the basic ratio of total assets to equity (sometimes called capital). Thus equity multiplier (EM) is expressed as:

$$EM = {}^{A}\!/_{E} \tag{1}$$

Where, A is total assets and E is equity. $ASSETS\ (A) = LIABILITIES\ (L) + EQUITY\ (E)$According to the asset growth model (Upneja and Dalbor (2001); Watson and Wilson (2002)), an increase in **A** must be financed by some source, either liability (**L)** or **E.** This concept conforms to the balance equation that, Assets equals Liabilities plus Capital (equity). $EM = {}^{A}\!/_{E}$ EM represents the amount of assets supported by each shilling of equity/capital and in this respect measures success in commercial financing that is at the centre of the prediction model. This EM ratio is also the inverse of capital ratio used by banks to evaluate financial distress and capital adequacy (Panday (1981); Whitaker (1999); Demirguc-Kunt, A. and Maksimovic, V. (1998); Pille and Parade (2002); Metwally, (1997); Ozkan, A. (2001)). An increase in EM indicates a higher level of commercial financing (**L**) or debt financing. The ratio therefore indicates the degree of financial leverage. This increase in financial leverage over time is defined as **LMA** (leverage multiplier added), and formulated as:

$$EM\ Rating\ (t+1) – EM\ Rating\ (t)\ \geq\ LMA \tag{2}$$

The equity multiplier rating gives a summary measure of how successful a MFI has been in attracting commercial financing. This indicates progress in commercialisation (defined as access to commercial funding or increase in **L** relative to **E**). LMA is maximised if EM rating increases from one period to the next. Success in commercialisation was therefore measured by the demonstrated increase of LMA (*t+1)* compared to the previous period at the MFI level.

Thus, the relative change in the LMA rating for two consecutive years over three years' time interval, between 1998 and 2003, was used to classify sample MFIs into successful and less successful in commercialisation (Hendricks & Singhal, 2001; Jain, 2001).

The binary classification was such that: MFIs with an increase in LMA rating in both period [1] and period [2] were classified as successful and coded **"1",** and those that showed a decline in relative LMA were grouped as less successful and coded **"0".** This measure resulted into classification of the sample into 55 successful and 48 less successful MFIs. Thus by use of the LMA rating, MFIs could be categorized as either having ability to succeed in attracting commercial funding or not.

*(b) Level **II** measure of success: commercialisation index*

The second level (II) measure of success was the commercial index. Commercialization at this level (II) was measured using an alternative success method; a composite index as opposed to the ordinal measure in (a), named commercialisation index or C-index. The C-index variables used emphasise bank traditional performance measures as well as non-financial factors such as transparent information reporting, customer satisfaction, sustainable growth and productivity (active clients), portfolio quality, and benchmarking critical performance to ensure good financial health of commercialising MFIs (Neely et al., 2000).

The C-index is a ranked measure of success estimated as a factor of several integrated financial performance measures (Neely et al., 2000). The performance measures convey relevant dimensions from the view point of a potential investor. The index aggregates 9 performance indices -$\mathbf{P}_{i\,1\text{-}9}$ and 15 measurement criteria - $m_{1\text{-}15}$, weighted on a scale of -12 to 12, centered at 0. The following are the indices:

1. Access to commercial funding. (Equity multiplier rating [*EMR*]- *m1)* **, P** $_{i\,1;}$
2. Sustainable growth rate (SGR). (Return on equity [*ROE*]- m_2-), (Total asset growth % [*TAG*] –m_3*),* (Return on assets [*ROA*]- m_4*)* **, P** $_{i\,2;}$
3. Service quality. (Number of borrowers [*NB*] – m_5*)*, **P** $_{i\,3;}$
4. Quality of portfolio (control for rapid growth). (Portfolio at risk [*PAR*]-m_6*),* **P** $_{i4;}$
5. Earning potential and long term viability of the MFI. (Net interest position [*NIP*]- m_7), (Return on equity [*ROE*]- m_2*), (*Inflation [*i*]- m_8*), (*Commercial lending rate [*lR*]- m_9*),* **P** $_{i\,5;}$
6. Country level of economic growth. [*GDP-r*]- $m_{10,}$*(*Growth-retrenchment [*G-R*]-m_{11}*),* **P** $_{i6;}$
7. Cashflow adequacy. (Internal cash ratio [*ICR*]-m_{12}*), (*Operating self sufficiency [*OSS*]-m_{13}*)* and, **P** $_{i7;}$
8. Financial distress and mortality risk. (Capital ratio [*CR*]-m_{14}*,* **P** $_{i\,8;}$

9. Financial reporting transparency/standard. (Information opacity/disclosure level [*OL*]-m_{15}) **P** $_{i\,9}$.

Table 1 below lists performance criteria variables, their definitions and selected references.

Table 1: Financial variables and investor criteria: C-index financial ratio variable description and predicted relationship with commercialization

Variable (*m*) definitions	Measure	Theoretical relationship, support
M_1- Equity multiplier rating ***(EMR)***	Financial leverage, access to commercial funds	+Ve; Kolari et al., 2002; Peyer & Shivdasani, 2001; Vasiliou & Karkaziz 2002
M_2- Return on equity ***(ROE)***	Profitability for shareholders and proxy for sustainable growth, and relative high growth potential	+Ve; Demirguc-Kunt & Maksimovic, 1998; Harris & Raviv, 1990; Vasiliou & Karkaziz, 2002; Hasan & Marton, 2003; Ozkan, 2001; St. John et al., 2000
M_3 – Total asset growth ***(TAG)***	Total funding gap and requirement. Portfolio investment proxy	+_Ve; Watson & Wilson, 2002; Vasiliou & Karkaziz, 2002; Upneja &Dalbor, 2001; Gibson, 2002; Demirguc-Kunt & Maksimovic, 1998; Hendricks & Singhal, , 2001; Watson & Wilson, 2002; Konish and Yasunda, 2003
M_4 - Return on assets (***ROA)***	Overall profitability of MFI	+Ve ; Kolari et al., 2002; Hussain & Hoque, 2002; Hasan & Marton, 2003; Demirguc-Kunt & Maksimovic, 1998; Ozkan, 2001; St. John et al., 2000; Vasiliou & Karkaziz, 2002
M_5 - Number of borrowers (***NB)***	Defines size, is sign of growth and good service quality. Proxy for effective demand	+Ve; WOCCU, 2003
M_6 - Portfolio at risk ***(PAR)***	Asset quality and riskiness of portfolio (loan default level) and/or measure of riskiness of MFI	-Ve; Jacobson & Robzbach, 2003; Barrios & Blanco, 2003; WOCCU, 2003; Pille & Parade, 2002; Clarence, 2001; MIX, 2006
M_7 – Net interest position ***(NIP)***	Earning potentiel	+Ve ; Hussain & Hoque, 2002
M_8 -Annual inflation (***i***)	Benchmark for high earning potential and good financial health. Adequate equity capitalization if ROE> ***i***	+Ve; Demirguc-kunt & Maksimovic, 1998

M_9 -Commercial lending rate (***LR***)	Benchmark for wealth creation and repayment capacity if ROE> ***LR***	+Ve; Demirguc-Kunt & Maksimovic, 1998
M_{10} -Gross domestic product (***GDP***)	Macro-economic expansion and level of development, control for country differences	+Ve; Jeng & Wells, 2000); Laitinen, 2002; Demirguc-Kunt & Maksimovic, 1998
M_{11} -Growth – Retrenchment ***(G-R)***	Portfolio investment overtime	+Ve; St. John et al., 2000
M_{12} -Internal cash ratio ***(ICR)***	Liquidity and cash flow adequacy	+Ve; Laitinen, 2002; Kang & Long, 2001; Metwally, 1997; Peyer & Shivdasani, 2001; Hasan & Marton, 2003; Berger et al., 1995
M_{13} -Operating self-sufficiency (***OSS***)	Cost coverage from operating income	+Ve; Hussain & Hoque, 2002; Ozkan, 2001; MIX, 2006
M_{14}- Capital ratio (***CR***)	Financial distress, mortality risk and capital adequacy.	-Ve; Laitinen, 2002; Demirguc-Kunt & Maksimovic, 1998; Pille & Parade, 2002; Metwally, 1997; Ozkan, 2001; Berger et al., 1995; Hasan & Marton, 2003; Konish & Yasunda, 2003; Barrios & Blanco, 2003; WOCCU, 2003
M_{15} -Opacity level (***OL***)	Level of information disclosure and transparency	+Ve; Berger et al., 1995; Myers & Majluf, 1984; Demirguc-Kunt & Maksimovic 1998; Watson & Wilson, 2002; MIX, 2006

Notation: + ve means the variable is predicted to have a positive relationship with commercialisation ; - ve, on the other hand, means the variable is predicted to have a negative relationship with commercialisation; ± ve means the variable can have either positive or negative effects on commercialisation. Variables (m_{1-15}) - represent profitability and financial distress (m_2, m_4, m_7 *and* m_{13}), capitalisation (m_{14}), credit risk (m_6,), liquidity (m_{12}), financial leverage (m_1), macro-economic factors (m_8, m_9, *and* m_{10}), sustainable growth (m_3, m_5 *and* m_{11}) and information disclosure (m_{15}).

The kind of variables included in the construction of the C-index relate to ability to earn sufficient profits and remain with enough cashflow to cater for the cost of borrowing. A number of authors have argued that as firms grow their earning capacity is likely to increase too (Upneja & Dalbor, 2001; Vasiliou & Karkazis, 2002; Ozkan , 2001). Applying this to the situation of MFIs, it is suggested that growth of MFIs makes them become significant players in financial intermediation for the poor and they acquire an increased debt capacity that often leads to higher profitability and further growth. Understandably, most MFIs have financial needs that exceed their internal resources and this underlines the demand for external resources and the need thereby to balance growth needs (Total asset growth % [*TAG*] –m_3) with equity).

However, demand for external finance leads to higher leverage. When leverage is high, the risks to shareholders are also high. Balanced growth therefore requires that the increase in leverage increases the cost of equity with just enough so that the weighted average cost of financing remains constant (Berger et al., 1995). The extent of external financing is determined by the control of financial distress and bankruptcy, thus bank regulators are typically concerned about the growth rate of assets and deposits of financial institutions (Kalari et al., 2002; Ozkan, 2001). Therefore the capital ratio [CR] (criterion measure-m_{14} above) must be kept within acceptable limits.

The C-index variables used therefore emphasise traditional bank performance measures, as well as non-financial factors such as transparent information reporting, customer satisfaction, sustainable growth and productivity (active clients), portfolio quality, and benchmarking critical performance to ensure good financial health of commercialising MFIs. It is believed that non-financial measures are better predictors of a firm's long-run performance and that they help managers monitor and assess their firm's progress towards strategic goals and objectives (Hussain & Hoque, 2002; St. John et al., 2000).

C-Index construction and modelling

The C- index is constructed by a scoring process of the 15 criterion measures -$m_{1\text{-}15}$ (financial ratio variables) grouped[1] in the 9 indices, with a weight and a commercial financial rating (CFR) score[2] assigned to each of the indices (Hendricks & Singhal, 2001; Laitinen, 2002). The 9 financial performance measures in the index have a maximum weight of 3 CFRs, except for the LMR measure (P i 1) which has a higher weighting of 4 CFRs. This way of combining the measures is intended to pay attention to and/or control the conditions specified by each performance indice. These conditions ensure that a MFI performs well and attracts commercial funding, but the intake of commercial capital is controlled to avoid a heavy debt load. Thus the index has built-in internal measures to ward off the potential risk of high indebtedness.

Time series data over three years (2001 – 2003) was used in index modeling as follows: the later two years (2002 – 2003) of data were used for the development of index measure and

[1] The purpose of this process was to capture the complexity that goes into determining commercial viability of a MFI given diversity of success factors across countries in Africa.
[2] The performance indices were transformed into a single financing rating score (CFR-score) that is sensitive to differences in the performance of a MFI with respect to its attractiveness to commercial lenders.

first year's (2001) financial information was used for predicting 2 year future success in commercialisation (Laitinen, 2002; Pille & Paradi, 2002; Kolari et al., 2002). Weights for the years 2002 and 2003 are the same, each with a weight of 1.The index values are obtained by the following formula for CFR scores:

$$\text{CIij}(Index\ 2002 - 2003) = \sum_{i=1}^{n} (\text{CFR Scores}) p^{1-9} m_j \qquad (3)$$

That is, [P i 1, P i 2,, P i 3, P i4, P i 5, P i6, P i7, P i 8, P i 9] *m* j }
Where CIij = Index of successful commercialization for the (P i) with performance indices for the *m* jth criterion measure.

The index assesses each MFI in the sample if the given 9 measurement criterion (critical performance for tapping commercial funding) for the performance indices has been met. A CFR score would be made for each performance indices based on fulfillment of the 15-criteria, for each year. The CFR-scores generated at each stage are cumulated until the end of the procedure. The summation of CFR scores for the 9 performance indices add up to the MFI grand C- index Score.

The **C-** index is thus measured in CFR scores and scaled from 0 – 25, with a maximum possible score of 25. The median score (**M)** under this scale is 13 CFR scores and this is the critical value for the binary classification. Classification was based on the Index values (or CFR scores), with the critical value of **0** (when weighted on a scale of -12 to 12, centered at 0) or median score of 13 CFRs as the cut-off. Higher CFR scores indicate the likelihood of successful commercialization, while lower scores indicate a high dependency on donations.

The Index was also conceptualized as a linear function of cumulative CFR scores for performance indices 1-9 minus the median; to arrive at normalized **CIij** Index.:

$$C - index = \sum_{i=1}^{9} CFR(\rho_i) m_j - M \qquad (4)$$

With the CI- index normalized, and a median score at zero to get a better visualization of the binary classification, the classification was such that if index exceeds zero an MFI was classified as "successful" and "unsuccessful "otherwise. The index therefore reflects the ease with which an MFI can tap capital from the wider financial market system, while maintaining performance sufficient for business excellence in microfinance.

The C- index measure of success was used to segment the sample of MFIs as "successful" or "less successful using the cut-off of 13 CFR scores. The segmentation using the index indicated those classified as successful coded as **"1";** while those scoring less than 13 CFRs (or index values < 0) as less successful were coded as **"0".** This classification resulted to 45 MFIs rated as successful and 58 rated as less successful.

Estimating the level of success (prediction model)

To further assess the LM rating rule and Ci- index ability to predict success of an MFI in tapping commercial capital, a logistic regression model was estimated by the method of maximum likelihood. As per the procedure in logistic modeling, the firms in the entire sample were classified into two groups. The dependent variable was converted into a dichotomous variable comprising those institutions that are more successful coded as (1), and those that are less successful coded as (0) for both sets of success measures (Liu, & Lee, 1997; Kennedy, 2001; Laitinen, 2001).

The purposes of this logistic analysis was to estimate the conditional probability that an MFI belongs to the category of commercializing institutions, identify significant predictors, and test the effectiveness of the models (LMA and CI index) in classifying the sample of 103 firms.. Future success in commercialisation was therefore measured for 2 years and predicted by the previous year's (2001) data using SAS logistic regression analysis. Thus, if effective, the C-index or the LMA will provide a useful commercial rating tool for preliminary screening of good commercial MFIs.

In the logistic classification model the variable (y) refers to MFIs that are successful in commercialisation. The probability of being successful is estimated by Prob (successful or y =1). This result, in turn, implies that the probability of a MFI belonging to the less successful category is-

$$prob(less\ \text{successful or y} = 0) = \text{Prob}(1 - \text{P}(\text{y} = 1)) \qquad (5)$$

The logic of discriminant analysis is formulated by the linear rating rule, namely classifying a MFI with characteristics given by the explanatory variables ($x_1, \ldots, x_n$) to category y equals 1 or 0, if the conditions are met. The logistic regression model estimated by the method of maximum likelihood can be formulated as follows (refer to Laitinen, 2002; Kolari et al., 2002; Kennedy, 2001) for expression of the generalised form of a logit function):

$$P(y = 1) = \frac{1}{1 + e^{-z}} \quad (6)$$

where: $z = b_0 + b_1x_1 + b_2x_2 + \ldots + b_n x_n$

y = the dichotomous dependent variable, successful commercialisation

P(y = 1)= the conditional probability of a MFI being classified as successful or less successful.

x_n = are the independent variables from 2001

b_0 = is an intercept term

b_n = the parameters for the logistic regression coefficients for predictor variables ($x_1, \ldots, x_n$)

e = the quantity 2.71828+, the base of natural logarithms

Independent variable description

The set of explanatory variables ($x_1, \ldots, x_n$) were selected based upon literature review. They were chosen because they have been used in prior studies and that the measures (or proxies) were readily available in the database used.

Table 2 provides a description of the independent variables used in this study and those included in the logit analysis. The list of predictor variables ($x_1, \ldots, x_{33}$) can generally be categorised into firm level financial parameters and non-financial performance indicators (St. John et al., 2000).

Table 2: Independent variables description and formulae

Predictor variables used in this study	(Notes, notation used in analysis)
X_1	Number of years since started operations (maturity, AGE)
X_2	MFI supervision by the National Central Bank (regulation, d_REGUL)
X_3	Registration form (legal structure, d_LFORM: fi, ngo, coop, bank)
X_4	Portfolio investment overtime or divesture (growth-retrenchment, d_GRPOST)
X_5	Profit margin (sustainability level, PROFIT)
X_6	Efficiency in operations (operating efficiency, OEXPR)
X_7	Earning potential of performing assets, cost saving ability (Earning Asset Ratio, EAR)
X_8	Number of borrowers (active clients – size, BORROWERS)
X_9	Portfolio size (dollar amount, SIZEGPF)
X_{10}	Information disclosure and level of opacity (information asymmetry, d_INFOTPR)
X_{11}	Asset quality and default risk (portfolio at risk, PAR)
X_{12}	Asset structure (net loans to total assets, ASETSTRUC)
X_{13}	Level of indebtedness, risk profile of MFI (debt equity ratio, GEARING)
X_{14}	Poverty outreach (average loan size in dollars, LONSIZE)
X_{15}	Poverty lending focus, depth of outreach (average loan size per GNI, DEPTHRCH)
X_{16}	Level of richness of country of operation (GNI per capita, GNI)
X_{17}	Economic stage of the country of operation (GDP growth %, GDP)
X_{18}	Pricing efficiency, economic cost of capital (annual inflation rate, INFLA)

X_{19}	Cost of funds/capital (market lending rates and/or 90 day treasury bills rates, LEDGRTE)
X_{20}	Size of equity, investor safety (equity to total asset %, EQBASE)
X_{21}	Level of savings on financing costs, increased earning potential (EAR*interest rates, COSTSAV)
X_{22}	Access to donations or quasi equity (main source of funding, d_DONOR)
X_{23}	Number of personnel, total staff level (size, PERSONEL)
X_{24}	Asset base (total assets, size, TASSETS)
X_{25}	Capacity to generate cashflow from performing assets (retained earnings/G Portfolio, EARNSUFF)
X_{26}	Operating self-sufficiency, (operating/operating/expenses, OSS)
X_{27}	Return on assets (net income/total assets, ROA)
X_{28}	Return of equity (net income/equity, ROE)
X_{29}	High earning potential, maintaining equity base(ROE>= inflation, d_FINHEALTH)
X_{30}	Maximising shareholder value, capacity to repay costly debt (ROE>=lending rates, d_RPMTCAP)
X_{31}	Fast growing MFI (TAG>=ROE, d_FASTGRO)
X_{32}	High growth prospects, enabling environment (TAG>=inflation, d_HGOP)
X_{33}	Relative access to commercial funds (d_LMR/CFR)

The prefix "*d_*" refers to the fact that the variable was operationalised as a dummy number or character.

The set consists of three types of independent variables. Firstly, it includes financial sustainability factors and traditional banking indicators such as sound banking practice and safety in lending. It is often said that "sustainability is the corner-stone of sound microfinance" (CGAP, 2002). The other variables reflects the critical performance indicators and benchmarks of the microfinance industry. Lastly, macro-economic factors are included to mitigate the differences between countries and to control both observable and unobservable time effects (Laitinen (2002); Demirguc-Kunt & Maksimovic, 1998). Unobservable characteristics that impact a MFI's performance would vary across MFIs and over time, but macro-economic variables are assumed to be the same for all institutions in a particular country at a given point in time.

There were in total 33 explanatory variables ($\mathbf{X}_1,\ldots,\mathbf{X}_{33}$). These variables cover the familiar lending criterions used for making investment decisions. Specifically, financing decision models for African MFIs are investigated. Given investors' sceptism of the African region, the study examines what it would take to finance MFIs from the capital markets and even by using private capital. Note that an industry level investors' perspective approach and basic performance indicators of sound microfinance are employed in the research methods.

Prediction model estimation

In this study, both the effectiveness of the 33 variables is examined in predicting future success in commercialization of African MFIs, and investigates a predictive model for successful commercialization. The main hypothesis for all the tests is: "Success factors differ for MFIs that are less successful in commercialization than those that are not". In order to obtain robust results for the predictive ability of the explanatory variables and sub-models, their performance was tested over different estimation methods. Two measures of success are investigated, the LMA and CI-index dependent variables both representing the likelihood of success with commercialization. The independent variables are drawn from the list of predictor variables in table 2 above.

(I) Data mining technique

Initially it was attempted to fit a logistic model estimated by the method of maximum likelihood on all the 33 independent variables. This was not possible because the data were too large to fit, as the system complained about the data (noisy data). Such a problem can lead to wrong estimations and or therefore misleading results. Random forests, which is a data mining technique is proven not to over fit, and thus provided a useful tool for tackling this data analysis problem (Breiman, 2001). Random forests (RFs), as part of decision trees[3] (DT), have become very popular because of their ease of use and interpretability (Lariviere & Van den, 2004, as well as their ability to deal with covariates measured at different measurement levels (including nominal variables). The random forests method also is less sensitive to system complaints (noisy data) compared to convectional logistic regression and discriminant analysis methods (Laviriere, B .and Van den Poel, D. (2004)).

Random forests model was used to synthesize/reduce the most important predictors from the 33 variables accurately for prediction purposes (Lariviere & Van den, 2004). Because of the small size of the sample and the need to preserve a degree of freedom, step-wise logistic regression procedures were applied to all the data. Besides investigating the binary classification problem and identifying the best predicators; other data analysis software applications like SAS, SPSS and STATISTICA were used in order to check robustness, benchmark RF results and use the results to develop a better prediction model (Konish & Yasuda, 2003; Pille & Paradi, 2002; Kolari et al., 2002). All the prediction models, regardless of application used were evaluated using the standard procedures outlined below.

(II) Models evaluation procedure

The multivariate models are evaluated to assess their predictive performance, based on the explanatory variables on the complete sample of 103 cases. Further, the performance of the

[3] A decision tree forest is an ensemble (collection) of decision trees whose predictions are combined to make the overall prediction for the forest.

models for each of the two dependent variables, the LMA and C- index, were benchmarked. The predictive ability of the models was evaluated based on the following measures:

(a) Model fitting (goodness of fit measure). This is the ability to fit a model for the explanatory variables. Researchers use a variety of measures (Kennedy, P. (2001)); such as -2LL measure under SPSS procedure (Mazzarol, 1998), the R square (Nagelkerke) percentage value, and Lanchenbruch cross validation method or the coefficient of concordance under SAS (Jain, 2001; Laitinen, 2001). If a model fits perfectly, the value for –2LL will be 0, otherwise the lower this value, the better. As the R square percentage value tends to 1 the better the goodness of fit. The higher the percentage of coefficient of concordance, the better the model fitting. A good model fit is considered important for the generalisation of the results. The coefficient of concordance and -2LL measures of fit are used in this study with critical probability value cut-off for all models as 0.05.

(b) Classification accuracy. This is the ability of the model to classify firms accurately. In the prediction models, this represents the number of $y = 1$, and $y = 0$ values, correctly predicted based on observed $P(y = 1 \text{ or } 0)$. Researchers (Jain, B.A. (2001); Laitinen, 2001; Mazzarol, 1998; St. John et al., 2000) use this criterion to evaluate how well the model classifies the data; Morison's proportional chance criterion (Jain, 2001) benchmark of 62.5%, percentage of correct classifications and lastly the overall percentage of correct classifications (Kennedy, 2001). The higher the percentage the better the model fit. All the measures were applied.

(c) Weighted efficiency. This criterion is defined as the weighted average of the overall correct classification rate, the percentage of successful correct classifications and the ratio of the number of correctly identified successful cases to the total number of MFIs predicted as successful (this includes misclassification due to type 1 error – classifying firms as successful when they are not). The closer this value is to 100%, the more effective the model is in predicting success. This measure was used to overcome some problems associated with the overall classification rate which can be misleading when the two classified groups (Jain, 2001) have significantly different proportions. In this case it was not a big problem as the binary response values were close; 48 for success cases, and 55 for less successful firms.

(d) The validation data set. The validation data set is obtained by splitting the data into 2 sets; a training set and a test set. The test set is used to validate how well the model executed the classification as per measures (b and c above). This applied to random forest, SAS and logistic regression by STATISTICA data analysis software system[4], Version 7.1.

Random forests technique

In this study random forest (RF) techniques are used to predict MFIs' success in commercialisation and to identify significant predictors. The random forests method[5] uses single classification trees where many trees are grown to form a forest, and each tree predictor in the forest depends on the value of some random vector (Breiman, 2003). To perform a classification, an input vector is stationed on each of the trees in the forest. Each tree then gives a classification, which as it were constitutes the tree's "vote" for that class. These votes are combined to make the overall prediction for the forest. The forest chooses the classification having the most votes (over all the trees in the forest). By this process the model estimates the variables that are important in the classification. In this study we select the random forests as proposed by Breiman (2001) which uses the strategy of a random selection of a subset of *m* predictors to grow each tree, where each tree is grown on a bootstrap sample of a training set.

Estimating the logistic regression model

Logistic regression was considered suitable for this study because of the existence of binary dependent variables. This procedure estimates the coefficients of a probabilistic model involving a set of independent variables that best predict the value of the dependent variable (Mazzarol, 1998). A positive coefficient increases the probability, while a negative value decreases the predicted probability of the outcome being investigated. Since the numbers of explanatory regressors were considered many (Cf. Table 2), a stepwise logistic regression analysis was performed (Laitinen, 2001). The logistic model was estimated by the method of maximum likelihood for all statistical packages used: SAS statistical package, SPSS, STATISTICA and even some regression forests as a test set after developing a training set. The logistic model used is specified in section 2.2.1 (also see Mazzarol, 1998; Laitinen, 2001).

EMPIRICAL RESULTS

The data sets and the relationship between the two dependent variables are tested for difference and correlation. The dependent variable rank correlation results are shown in Table

[4] See Statsoft, Inc. (2005), www.statsoft.com
[5] The theoretical underpinnings of the random forests program are laid out in the paper "Random Forests" by Leo Breiman and Adele Cutler. It's available on "Random Forest reference manual", http://ucsu.colorado.edu/_breitenm/. Also found in http://oz.berkeley.edu/users/breiman/Using random forests V3.1.pdf.

3. The correlation result of 44.4% indicates no significant relationship, but a crude relationship between the C- index and an increase in financial leverage (LMA).

This result is not surprising, given that the C- index does not only measure the increase in financial leverage but also success in commercial microfinance. The binary classification for the LMA can only be used to give a naïve measure of success without the combination of critical factors necessary for successful commercial microfinance. This supports the conjecture that successful commercialisation is more than just gaining access to commercial funding.

Table 3: Relationship between C-index and LMA

CI- Index	**Marked Cells have counts >10. Chi-square tests: p=0.1081**		
	LMA (0)	**LMA (1)**	**Row Totals**
0	23	35	58
Row %	39.66%	60.34%	
1	25	20	45
Row %	55.56%	44.44%	
Total	**48**	**55**	**103**

Multivariate logit models

Four separate analyses were conducted. First, the relationship between the full set of independent variables and the two binary success measures were modeled. Then a sub-analysis of different sub-models was performed to investigate the relationship between a cluster of variables representing important hypotheses and commercialisation (these hypotheses were obtained from preliminary results, e.g. the relationship between commercialisation and the sustainability of microfinance, mission drift, etc). For each of these tests the hypothesis, with respect to the two binary classification variables (LMA and C- index), are:

H (1) that a MFI belongs to the successful category given by *y =1* while the null hypothesis is,

H (2) that the MFI belongs to the less successful category, *Prob (1 - P(y =1))* given by *y =0.*

For the random forests data mining technique and STATISTICA approach, the model is built on the same training set (60% of the entire sample) and then tested on the cross-validation set of 43 MFIs. The data sample split was random. The cut-off point of 0.005 was derived by classification trees under RF. But, under the SAS procedure the data was split into training (70%) and test sample (30%) sets. The F-to-enter and F-to-delete significance levels were developed (by default) on SAS as 0.05, while it was necessary to drop these to 0.2 for the LMA fitted model. The application of the model to the test data set gives an independent goodness of fit measure and helped in evaluating how well the model did the classifications. Only the classification matrixes for the “test results” are shown. Analysis results and evaluation for random forests on the full model are reported in Table 4.

Table 4: Random forests performance results

Dependent variable (C- index)			Predicted cases (test set)		
		Actual cases	**1`s**	**0`s**	Percentage correct
Successful	**(1`s)**	20	16	4	80%
Less successful	**(0`s)**	23	6	17	74%
TOTAL cases		43	22	21	
Overall correct classification					77%
Weighted efficiency					76%

There were 43 cases in the test sample and when the random forests technique was applied to this set, 16 of the 20 1's (80%) were classified correctly. The overall correct classification is 77%, which is higher than the 62.5% obtained by Morrison’s chance criterion (Jain, 2001). The weighted efficiency of the full model is 76%. Thus the overall model seems to fit well with high prediction accuracy. These results indicate that the variables used in the prediction are significantly related to commercialisation. The test revealed that one variable, ROA, was able to classify 78% of the 0’s and 70% of 1’s correctly, which means that the ROA can be used on its own to identify which MFIs will not succeed in commercialisation.

With regards to the most important predictors in the model, the top seven were highlighted in Figure 1. These variables relate to profitability, macro-economic factors and institutional risk profile.

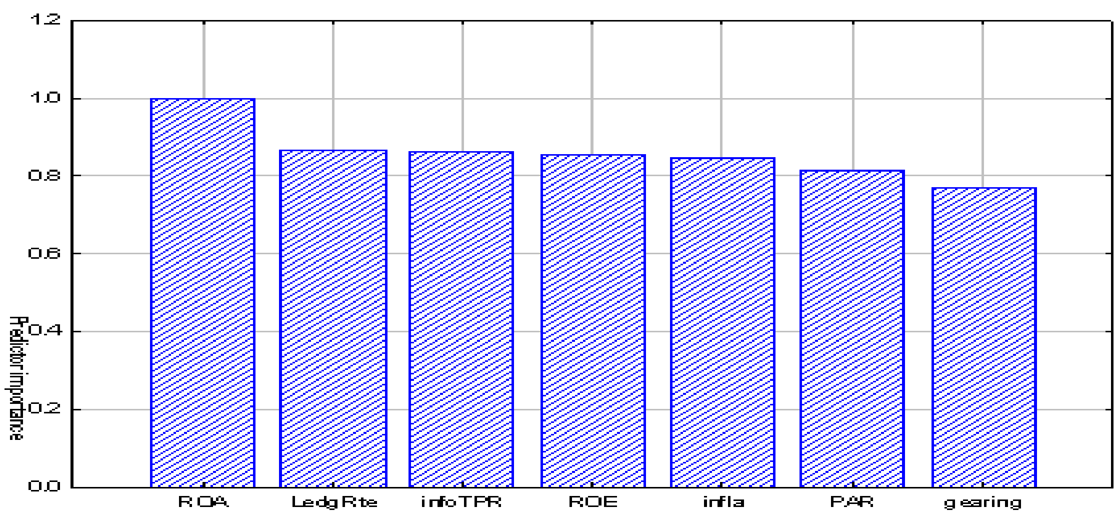

Figure 1: The seven major predictors for success in commercialisation

Table 5 presents LMA estimated statistically significant factors associated with commercialisation for the entire sample under SPSS technique by stepwise regression. The estimation for C- index failed due to too many variables. For LMA the estimation terminated at iteration number 7. The cut value is 0.500. The probability modeled is LMA=1. The final model included 8 significant variables.

Table 5: Binary logistic regression results, SPSS modeling LMA

Explanatory variables	ß estimâtes	Wald	*p*- Values
REGUL(*Yes*)	1.884	4.028	0.045**
LFORM	0.000	4.799	0.187
G-RPOST(G)	-1.498	3.602	0.058*
EAR	-0.020	1.754	0.185
BORROWER	0.000	1.937	0.164
PAR	0.104	2.939	0.086*
GEAING	0.001	2.650	0.104
LEDGRTE	0.081	2.182	0.140
EQBASE	0.072	4.472	0.034**
PERSONEL	-0.009	3.777	0.052*
EARNSUFF	0.063	3.183	0.074*
OSS	-0.049	5.221	0.022**
FINHEALT	5.401	8.859	0.003***
CFR	-0.213	1.652	0.199
Constant	0.091	0 .001	0.981
Notes: *** Very significant, *p*<1% ; ** *p*<5%; * *p*<10%			
Goodness of fit:		-2 log likelihood	84.137
Explanatory power:		R Square	57.6%

Classification table for overall goodness of fit

LMA		LMA predicted cases		
Observed cases		**0`s**	**1´s**	Percentage correct
0´s	48	36	12	75.0 %
1´s	55	8	47	85.5
TOTAL	**103**	44	59	
Overall correct classification				80.6%
Weighted efficiency				81.9%

The results show that one variable (financial health or earning potential) is particularly significant at the 0.01 level, while three others (operating self-sufficiency, regulatory status and size of equity) are significant at the 0.05 level. This is not surprising, as it suggests that investors are currently worried about the financial health of investing institutions, as to whether they earn enough to capitalise their equity base and whether the equity base provides enough safety.

The fitting of the model (R-square) shows that predictor variables can explain 58% of successful predictions. However, the binary classification, which gives the overall goodness of fit for the model, was able to classify successful commercialisation correctly at a rate of 85.5%. The weighted efficiency is 82%, while the overall correct classification for the model is 81%. The performance of the estimated logit model is satisfactory, taking into account the high accuracy predictions results as indicated.

To improve the strategic fit of the models, a reduced data set model including only 15 variables was tested. The variables used in this model were obtained from a preliminary analysis. The results are presented in Table 6 for both the LMA and C- index.

Table 6: Binary logistic regression reduced set results, SPSS modeling

	C- index		**LMA**	
Explanatory variables	ß estimates	*p*- values	ß estimates	*p*- values
LFORM (NGO)	-0.000	0.828	0.000	0.188
LFORM (FI)	-0.882	0.402	0.310	0.674
LFORM (Bank)	-0.140	0.902	-0.438	0.594
LFORM (Coop)	-0.596	0.620	1.295	0.137
OEXPR	0.000	0.995	0.012	0.273
EAR	0.007	0.207	0.001	0.692
INFOTPR	1.528	0.002***	-0.065	0.814
PAR	-0.034	0.269	0.071	0.033**
ASETSTRU	-0.023	0.199	0.006	0.744
GDP	-0.018	0.880	-0.062	0.546
EARNSUFF	0.019	0.492	0.024	0.177
OSS	-0.017	0.188	-0.024	0.048**
ROA	0.093	0.041**	0.027	0.349
ROE	-0.019	0.052*	0.001	0.856
FINHEALT	1.118	0.3141	0.818	0.029**
RPMTCAP	2.192	0.007***	-0.486	0.475
FASTGRO (`1)	-4.571	0.207	0.141	0.899
HGOP (`1)	-7.689	0.740	-0.359	0.747
Constant	-2.764	0.218	1.538	0.349
Notes: *** Very significant, *p*<1% ; ** *p*<5%; * *p*<10%				
-2 log likelihood		70.623	118.751	
R square		66.5%	27.3%	
Overall correct classification		83.5%	66.0%	
Weighted efficiency		82.4%	66.5%	

Classification table for overall goodness of fit

C- index Observed cases		C- index predicted cases		
		0`s	**1´s**	Percentage correct
0´s	58	48	10	82.8 %
1´s	45	7	38	84.4
TOTAL	**103**	55	48	

LMA		LMA predicted cases		
Observed cases		**0`s**	**1´s**	Percentage correct
0´s	48	33	15	68.8 %
1´s	55	20	35	63.6
TOTAL	**103**	53	50	

The model singled out information disclosure and repayment capacity for commercial loans as the major considerations for investments in African MFIs. The percentage of successful MFIs correctly identified is 84.4%, and the overall correct classification is 83.5%, while the weighted efficiency is equally high at 82%. The -2 log likelihood measure shows an improvement in model fit from the full model by LMA, posting a value of 70.623. The C- index has more explanatory power (R- square) at the rate of 67%. Overall the model fits very well and suggests that information opacity and earning potential are good predicators of commercialisation.

The LMA reduced model seems to have lost its sting with its explanatory power by dropping to 27%. However, the model is very consistent as it still manages to identify the financial health of institutions, operating self-sufficiency and portfolio quality as the most important predictors of current access to commercial funds. The C- index suggests that investors will be attracted by MFIs with an ability to not only cover economic costs (inflation) and maintain value for equity in real terms, but also with the capacity to replace soft loans with loans charged at market interest rates and making money for the shareholders.

To achieve a reduced data set for SAS logistic regression, it was necessary to carry out a principal component analysis. This was conducted for 22 financial variables that upon analysis were found to have significant differences. The factor analysis resulted in a five factor solution based on eigen-values greater than 1 (criteria per Kaiser's rule) under various combination procedures for each factor (Lee & Liu, 1997). The five factors were then transformed into factor scores and consequently used to construct success classification models, as suggested by Jain (2001) and Liu and Lee (1997). The results are reported in Table 7.

Table 7: Binary logistic regression results, SAS modelling

	C- index		**LMA**	
Explanatory variables	ß estimates	*p* -Values	ß estimates	*p*- Values
Intercept	1.7150	3.32%	0.0278	0.9337
FACTOR 1	-0.9727	2.28**		
FastGro (*NO*)	1.8014	1.94**		
RpmtCap (*`0*)	0.8149	0.38***		

FACTOR 2	0.9068	1.63%**
FACTOR 5	0.7193	1.45**
FinHealth (‘0)	0.5336	10.11
Grpost (G)	0.5068	4.70**
Lform (Bank)	1.0977	4.84**
Lform (Coop)	0.7304	9.38*
Lform (FI)	-1.3834	0.77***
Regul (No)	0.7569	1.47**
Notes: *** Very significant, *p*<1% ; ** *p*<5%; * *p*<10%		
-2 log likelihood,	= 109.972	118.088
Pearson Goodness of fit test, *p* value	= 0.5758	0.2006
Deviance test, *p* value	= 0.3988	0.0471
Coefficient of concordance	= 82.2%	76.1%
Contingency coefficient, c	=0.824	0.762
F- to-enter significant level	= 0.05	0.20

The most significant variables in the C- index logistic model are repayment capacity for commercial loans (Rpmt cap), growth opportunities (FastGro) and underlying critical success factors in FACTOR 1 (Cf. Table 8 for loading predictors). This result is interesting as it confirms other research findings that profitable and fast growing MFIs need external finance (Upneja, & Dalbor, 2001) that may have to be sourced from the capital markets. This underscores the necessity for this category of MFIs to link with the wider financial system for continued funding.

With respect to the LMA results, they suggest that lack of access to commercial capital is closely associated to unregulated MFIs, and institutions not registered as NGOs, but bear other legal status like cooperatives, financial institutions or banks. Contrary to popular belief, a NGO has had a particular attractiveness to new investors. This is understandable, given fact that these are the pioneers of microfinance and most social investors look for excelling NGOs that have mastered the art of microfinance.

Table 8: Summary factor solution, SAS modelling

Model Var.	Profit	OExpR	EarnSuff	OSS	ROA	ROE	Borrowers	SizeGPF	Personel	Tassets	LonSize	DepthRch
Factor 1	0.60	0.78	0.92	0.81	0.89	0.72						
Factor 2							0.79	0.88	0.78	0.90		
Factor 5											0.72	0.52

The LMA model fields in 2 critical success factors: FACTOR 2 representing the growth model, and FACTOR 5 for the social mission model. FACTOR 2 includes dimensions emphasising the importance of size in commercialisation. However, the effects of size on the logit are positive. This suggests that although SIZE has been a consideration in accessing commercial funding for MFIs in Africa, only small firms have benefited from investors than bigger MFIs.

Finally, the results support the conjecture that commercialisation is associated with bigger loan sizes and confirms the fears of microfinance traditionalists who strongly belief that the microfinance intervention should seek to address the social-economic problems of inequality and lack of opportunities. In this case, commercialising MFIs seem not to target their financial services to the poor who only borrow small size loans.

It is clear from Tables 6 and 7 that the index provides better prediction accuracies compared to the LMA logistic regression model. For all cases of binary classification tests, a significant and better performance in favour of the C- index (Cf. -2 log likelihood, its lower for index, the Pearson goodness of fit test and deviance show better fitting of the model with higher p-values) can be observed. The coefficient of concordance or percent of correct classifications for the LMA is moderate at 76% while for the C- index this goodness of fit rating is very high at 82%. The overall prediction accuracy is 82.4% (vs. 76.2% for LMA). This statistically means that on the basis of the C- index, the information in 2001 can be evaluated by this logistic rule and correctly classify 82 MFIs out of 100 into successful or less successful during 2002 – 2003. The following section reports the sub-model analysis results that were done to further validate the model and best predicators of commercialisation.

Sub- analysis logit models

We show results of the STATISTICA technique for six sub-models and validation tests[6] for the predictive ability in both the LMA and the CI-Index. The sub-models are based on general intuition of the author and not on any scientific grouping procedure. The six sub-models are: (1) Sustainability model which groups the following variables: Profit, EAR, CostSav, EarnSuff, OSS, ROA,ROE, finhealth, Rpmtcap. (2) Outreach growth model which groups the following variables: Grpost, borrowers, sizeGPF, personel, Tassets, fastgro, HGOp. (3) Macro-economic model which groups the following: GNI, GDP, infla, LedgRte, donor, (4) Firm Model, which groups the following variables: Tassets, Eqbase, gearing, infoTPR, Lform, regul, lonsize,

[6] The sample data was split into two: 60% for the training set and 40% for the test set. The results are for the test set only.

EAR, age. (5) Efficiency model, which groups the following: OexpR, PAR, AsetStruc, CostSav. (6) Social model, which groups the following: GNI, lonSize, depthRch.

Table 9 reports the results of the sub-models. From the results one model stands out from the C- index with improved classification over the SUSTAINABILITY model. That is, the FIRM model; which is significant showing an overall classification accuracy of 79%, correct classification of 80% and a weighted efficiency of 78%. This demonstrates the importance of financial information disclosure for future access to commercial capital.

A sub-analysis of four models was also carried out: best fit, common variables, critical success factor and social misfit model. These models came as a result of strategic groupings established by the author of various variables which were subjected to logistic regression using two techniques. The training set of data (70%) was used to fit the models under SAS while there was no split of the data under the SPSS modelling for the sub-models. This comparative analysis is intended to identify the most important and outperforming prediction model as per the evaluation criterion set in this study. SPSS evidence is reported in the summary performance, Table 10. The test results indicate two very significant variables for the best fit sub-model, but the results of other sub-models are not impressive.

The analysis of the sub-models were also done under the SPSS technique for all, but only results of the best fit model modelled for the C- index are shown in Table 11.

Table 9: Cluster sub-model analysis, STATISTICA modeling

Logit model	Sig. Y/N **CI Index**	ROE %	TPR %	Ass. Struc. %	Correct classification %	Overall classification %	Weighted effici. %	Sig. Y/N **LMA**	Borrowers %	port. %	Regulation %	Correct classification %	Overall Classification %	Weighted Efficiency %
Sustainability	Y	3.7			60	77	74	N				21	42	46
Outreach	N				25	53	43	N	9.5	6.5		71	65	67
Macroeconomic	N				30	53	44	N				72	53	66
Firm	Y		7.6		80	79	78	Y			6.3	36	49	52
Efficiency	Y			6.8	60	63	61	N				12	37	36
Social	N				0	51	17	N				64	53	60

Table 10 Cluster sub-model analysis, SAS modeling

Logit model	Model fit- Y/N **C- index**	ROA %	Info TPR %	Fast gro %	Rpmt cap %	Inflation %	Loan size	Correct Classification %	Overall classification %	Coeffi. concord. %	Model fit- Y/N **LMA**	Factor 2 %	Coeffi. concor. %
Best Fit	Y	1.5	0.0	1.6	0.0	4.5		85.71	87.1	89.8			
Common var	Y		0.0	0.9	0.0			78.57	90.32	80.7	N		
CSF	N										N	5.6	67-1
Social	N						8.6			59.4	N		59.9

Table 11: Binary logistic regression results, best fit SPSS sub-model

	C- index	
Explanatory variables	ß estimates	*p*-values
INFOTPR	1.509	0.001***
INFLA	0.009	0.074*
OSS	-0.019	0.081*
FASTGRO (1)	-4.934	0.059*
RPMTCAP (1)	2.500	0.001***
Constant	-4.613	0.008 ***
Notes: *** Very significant, *p*<1% ; ** *p*<5%; * *p*<10%		
-2 log likelihood	77.899	
R square	61. 5%	
Correct classification	77. 8 %	
Overall correct classification	80. 6%	
Weighted efficiency	78. 7%	

The sub-analysis allowed for the separate control of the effects of association of the variables that mask and cloud the visibility of others. In the reduced variables sets, the best fit model emerged successful in predicting future success in commercialisation, in all the sub-models. A high of 90% coefficient of concordance (or 87% classification accuracy) was achieved compared to just 82% prediction accuracy when all 33-variables were used,

SUMMARY AND CONCLUSION

This paper showed the empirical results of test hypothesis of the variables which influences access to commercial capital and integration to the financial markets in the next two years. The key determinants of access to commercial capital are information transparency, repayment capacity, cashflow adequacy ROA, fast growth, and inflation. Social variables were predictors of less successful commercialisation. Compelling evidence is shown to prove that the

C- index as modelled is a useful tool in predicting the future success in commercialisation of microfinance. The use of various techniques and sub-analyses helped in providing rigour and added improvements in the results in terms of accuracy in identifying key predictors of success by benchmarking the random forests data mining results, STATISTICA and SAS, against those obtained by SPSS logistic and linear regression models. The best logistic model had a satisfactory goodness of fit (coefficient of concordance) and overall classification accuracy of 90% and 87% respectively.

In modelling the various relationships of the 33 predictors with success in commercialisation, various hypotheses, in the form of sub-models, were considered. These sub-models represented possible synergy effects of various variables and/or interactions. The findings support the hypothesis that, a MFI's mission and its overall sustainability (profitability and liquidity) strategy and growth prospects, coupled with adequate disclosure of financial reports, is associated with successful commercialisation. Association among economic and social variables will play a minimal role in differentiating who gets funded and who does not attract commercial capital. The results suggest that investors and funding agencies will value superior earnings on invested capital in the microfinance industry and prefer MFIs that operate in an environment which supports growth opportunities and low inflation trends.

The research also found strong support to the hypothesis that the C- index is a better measure of successful commercialisation than the LMA (leverage multiplier added*)*. It appears that the integration of various factors comprising the index was useful in giving the index its sting. Although this is the first attempt to model commercialisation, these results suggest that the C- index commercial rating rule has superior predictive abilities that could be explored to guide screening efforts for winners, investment decisions and other binary classification investigations*.* These results obviously imply that it is possible to develop a uniform commercial success prediction rule for MFIs in Africa that would give useful information to investors. The model will also be useful in guiding successful commercialisation schemes in Africa because it provides MFIs with a structured approach for achieving sustainable commercial microfinance.

Besides exploring the information requirements for commercial investors in determining investment priorities, this paper tested one of the major contentions in microfinance debates, the mission drift theory or social model in the sub-analysis. Results suggest commercialisation leads to abandonment of the plight of the poor in search for more profits. By this argument it is indicative that commercialisation destroys the long-term social value of microfinance as a development strategy and a poverty reduction tool. Assuming that the funding constraint holds the key to continued intervention and growth of the microfinance activity, and that available options are in pursuit of a commercialisation strategy, then successful commercialisation is important for MFIs to remain relevant.

For further studies on similar prediction models attention should be paid to amount of data and a longer series for empirical analysis. Only time series data of 3 years was available, thus permitting data for only one year to be used in predicting 2 year success of the MFIs. Notwithstanding, in the current study we gained sufficient insight for good suggestions on how to effectively tap and benefit from commercialization strategies.

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