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Abstract

This study investigates the legitimacy of the relatively high interest rates charged by those microfinance institutions (MFIs) which have been transformed into regulated commercial banks using information garnered from a panel of 1232 MFIs from 107 developing countries. Results show that formally regulated micro banks have significantly higher average portfolio yields than their unregulated counterparts. By contrast, large-scale MFIs with more than eight years of experience have succeeded in lowering interest rates, but only up to a certain cut-off point. The implication is that policies which help nascent small-scale MFIs to overcome their cost disadvantages form a more effective pricing strategy than do initiatives to transform them into regulated institutions.

JEL classification: G21; G23; G28; E43, N20
Key words: Microfinance, microbanks, non-bank financial institutions, interest rates, age, economies of scale, developing countries

INTRODUCTION

The global microfinance movement has received intense media attention in the past decade. This has thrown the spotlight on two key concerns. The f*irst* is the high interest rates charged by microfinance institutions (MFIs) by comparison with formal sector commercial banks, raising allegations of monopolistic pricing (Rosenberg *et al,* 2009; Yunus, M, 2011). The *second* is related to fears of "mission drift" as many MFIs transform into regulated profit

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maximizing banks with a consequent re-orientation in their services towards the better-off among their poor clients in order to achieve financial self-sufficiency (Hartarska and Nadolnyak, 2007; Frank, 2008; Tchakoute-Tchuigoua, 2010; Mersland and Strøm 2010 and Roberts, 2013).

In the early years, pioneers in microfinance lauded the promise of providers to reduce poverty and engineer social change in communities by lending to and collecting savings deposits from extremely poor households which lack the collateral to secure loans from formal-sector commercial banks. However, in the recent past, some advocates of microfinance as a development strategy have embraced the idea that the opportunity to achieve a sustainable large-scale programme lies in approaches which encourage MFIs to adopt traditional banking practices with related regulatory requirements, even if this entails charging higher cost-covering interest rates (Churchill and Frankiewicz, 2006; Ledgerwood *et al*, 2006; Sundaresan, 2008; Cull *et al,* 2008 and 2009). Such formalisation should instil confidence in the system and attract capital to fund investments in technology, equipment and staff training (Armendáriz and Morduch, 2010). Moreover, Robinson (2001), Drake and Rhyne (2002), Dehejia *et al* (2007) advocate that the integration of micro financial services into the formal sector should enhance the growth and capability of MFIs to provide a higher quality of products including larger loans to an ever-growing number of beneficiaries around the world without a continuing reliance on subsidies.

Ultimately the interplay between the characteristics of MFIs and the nature of the aforementioned concerns in the debate is an empirical matter. Unfortunately, these important issues have remained largely untested, primarily because of a lack of variation in the pattern of interest rates charged by different institutions. In this paper, we resolve this difficulty by using a panel framework comprising 1232 financially self-sufficient MFIs from 107 countries across six developing regions from the Microfinance Information eXchange (MIX) database[2].The decision to focus on financially "successful" MFI's derives from the argument by Rosenberg *et al* (2009) and Cull *et al* 2009 that the inclusion of subsidized unsustainable MFIs substantially lowered the average interest rates reported in previous studies. Nonetheless, Cull *et al* (2009) found that the correlation between financial outcomes in terms of operationally self-sufficiency (OSS) and financial self-sufficiency (FSS) is positively

[2] The Microbanking Bulletin (MBB) defines a financially sustainable MFI as an institution where inflation adjusted financial income minus monetary and in-kind donated goods, technical assistance and other services exceeds the sum of inflation adjusted operating costs, impaired losses on loans and financial expenses arising from both the actual and predicted costs of acquiring goods and services for which it is not paying a market rate.

significant at circa 0.89. Such a high correlation, although not perfect, indicates that the two measures of financial performance are somewhat interchangeable.

This study contributes to the microfinance empirical literature in two ways.

First, it investigates whether the annual average interest rates observed for financially self-sufficient (FSS) microfinance institutions with the legal entitlement to conduct traditional banking activities are significantly higher than the rates charged by MFIs with a different charter status. We differentiate between the interest rate income of rural and other microbanks (MICROBANKs) vis-à-vis those of non-governmental institutions (NGOs), non-bank financial institutions (NBFIs) and credit unions/cooperatives located in Sub-Saharan Africa, North Africa and the Middle East, Eastern and Central Europe, East Asia, South Asia and Latin America regions[3].The results should highlight the responsiveness of microcredit interest rates to changes in the regulatory frameworks which oversee the practices of microfinance banks in developing economies. A similar empirical study by Campion *et al* (2010) examined the relationship between operational self-sufficiency (OSS) and a measure of portfolio yield in a study of twenty-nine institutions in seven Caribbean countries from 2005 to 2008. However, their study was constrained by data and methodological issues. This paper reduces these limitations by increasing the number of institutions, countries, time period of study and by the use of a more rigorous econometric method.

Second, statistics show that MFIs which are classified as financially self-sufficient institutions by MIX analysts tend to be older with larger levels of lending. We therefore investigate the interaction between interest rates, scale economies and years of experience of microcredit providers. The outcome of this analysis should help reveal the extent to which policy actions which promote the learning which comes from years of practice and growth in the scale of an institution's loan operations are likely to be more effective pricing strategies than initiatives which encourage microfinance institutions to transform into banks.

The paper is organised into four sections. Section I provides an overview of annual average interest rates of those financially self-sufficient MFIs which were consistently reported in the MIX developing country database from 2005 to 2010. We further compare the variation in these annual average interest rates for selected MICROBANKs versus those of NGOs, NBFIs and credit unions. Section II outlines the empirical research model, hypotheses

[3] Choice of MFI charter types and regions is based on the classification by the Microfinance Information eXchange (MIX) 2009.

and the basic features of our estimation method. Section III presents the results of our empirical analysis and further explains the implications of age and scale of operations for MICROBANKs and their clients where average interest charges are concerned. Section IV draws conclusions with related policies from the empirical findings.

I. Data Description

Our argument here is conducted under: (i) sample selection, (ii) sample distribution and (iii) microcredit interest rates.

1.1: Sample Selection

In this section, we summarise the pattern in the actual annual average interest income earned by our different types of financially self-sufficient MFIs of different age and scale between 2005 and 2010 using a standard descriptive statistical method. The choice of time-span considered is limited by the availability of time series data on interest yield and its four major components — cost of funds, operating costs, loan loss provision rate and profits[4].The information on these variables is obtained from the MIX website only so as to ensure conformity and reliability in their measurement. Notwithstanding these benefits, Cull *et al* (2007), Gonzalez (2007), Cotler and Almazan (2013) and Nwachukwu (2013a) expressed concern regarding the self-selection bias inherent in the MIX dataset. They noted that the more successful MFIs with adequate information systems are more likely than others to expose their private financial accounts to external examination and to satisfy the minimum requirements of auditing firms and MIX analysts. In an anticipatory variation of the uncertainty principle, the knowledge that they will be closely observed by financial analysts, will further improve the quality of their submission. Nevertheless, the MIX database is commonly used in the microfinance empirical literature on the assumption that those institutions which report to the organisation collectively serve a sufficiently large fraction of active microcredit users worldwide.

Annual data on interest yield and its above-mentioned four key components is available for 1232 sustainable micro lenders located in 107 countries throughout our six developing regions. These comprise those institutions reporting on these crucial variables for at least three out of the six years of study. Given the time period considered and the number

[4] According to Gonzalez (2010), the formula for MFI interest income is expressed as follows: Interest + fee income from loans and other financial services = Cost of funds + Loan loss expense + Operating expense + Profit + Tax minus Income from non-financial activities.

of data points which these institutions reported to MIX, we were able to generate an unbalanced cross section-time series panel data of 3980 observations. Appendix Table 1 reports the mean for all the variables which underlie our analysis for our five classes of MFIs subdivided across their age and scale of their lending operations.

1.2: Sample Distribution

Figures 1A and 1B show the distribution of our dataset across the different types of our sustainable microcredit providers, as well as in terms of their age and scale of operations in that order. Figure 1A shows that our sample of study is dominated by NGOs and NBFIs. Collectively, these supposedly socially-orientated MFIs make up two-thirds of our sample. The fact that these MFIs form the largest proportion of our dataset, and by inference that of the microfinance sector as a whole, should not be a surprise. This indicates that the recent concentration on microbanks in the media does not merit their relative importance.

As shown in Figure 1B, the majority of financially-viable NGOs are mature, small to medium scale programmes with gross profit margin in excess of 40 percent. By contrast, more than half of our NBFIs, which may include registered moneylenders, micro-insurance firms, micro-equity institutions, pawn shops, payday lenders, check cashing firms and currency exchanges, are probably new initiatives which have mostly been set up in the past five years by large-scale institutions. Their profit margins are evenly spread across our chosen three sub-samples of profitability. This is probably an indication of the wide diversity of type and number of institutions, financial contracts, products and services offered.

Figure 1A: The Distribution of Financially-self sufficient MFIs in our Sample by Charter Type

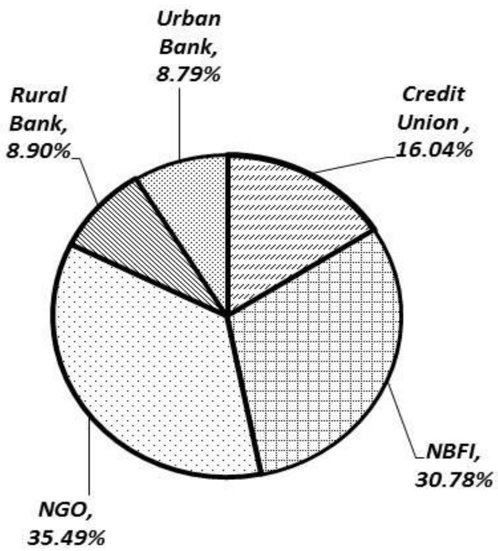
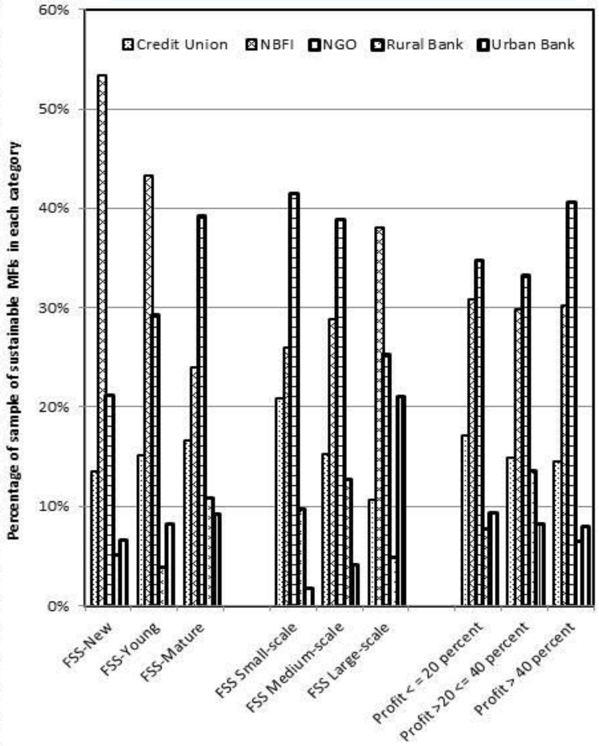


Figure 1B: Distribution of Dataset by Age, Scale and profitability of Financially self-sufficient MFIs



1.3: Microcredit Interest Rates

The yield on microloans (YLD) is calculated by MIX analysts as the sum of all interest, fees and commissions actually received by an MFI weighted by the size of its outstanding gross loan portfolio (GLP) averaged over the period of study. Figures 2A and 2B show the annual average interest income earned by our financially viable MFIs reported by the type, age and scale of their operations respectively. We use nominal rather than real interest yield in order to capture the higher risk of defaults, costs of administration and other complications faced by MFIs which charge the comparatively high interest rates which cover inflation. In any event, as observed by Woller and Schreiner (2002), the nominal portfolio yield is highly positively correlated with the real yield. Thus, nominal rather than real portfolio yield is widely used in the literature as a proxy for the actual interest rate charged on loans.

The statistics in both figures 2A and 2B indicate that the annual average interest income for a typical financially self-sufficient MFI in the MIX developing country database (hereafter referred to as MIX-MFI) was 32.86 percent of gross loan portfolios (GLP) outstanding. This is comparable with the mean real gross portfolio yield of 35.4 percent reported by Cull *et al* (2007).

Figure 2A: Yield on Gross Loans for MFIs of Different Ages

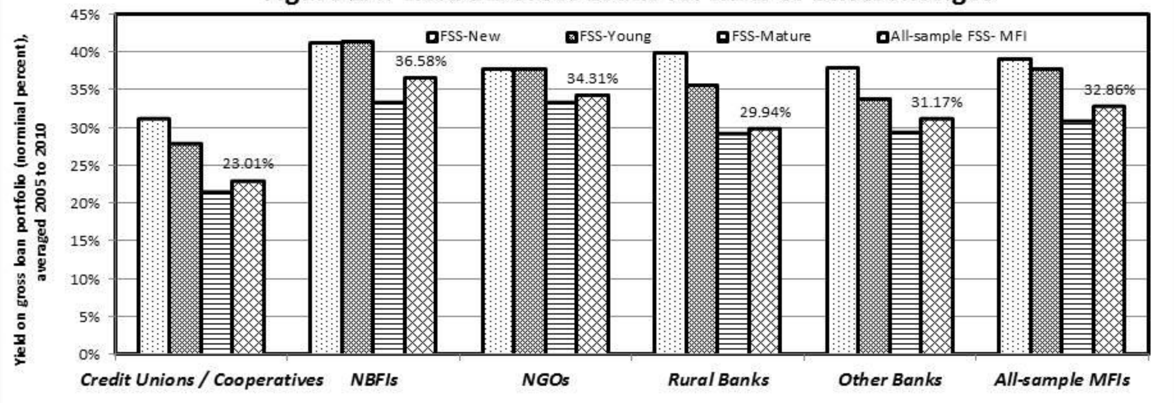
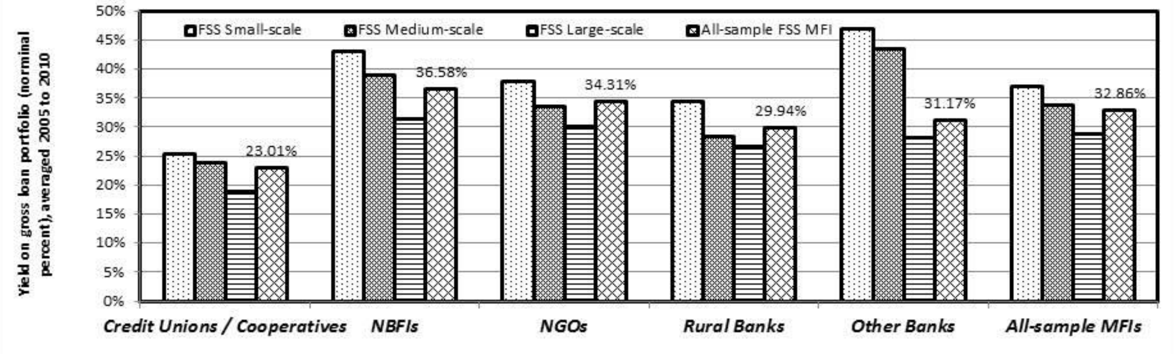


Figure 2B: Yield on Gross Loans for MFIs of Different Sizes



A disentangling of data by type of MFI shows a wide variation in the average interest rate charged. Contrary to popular belief, the highest average interest rates of between 34.31 percent and 36.58 percent per annum were observed for NGOs and NBFIs in that order. This is presumably because NGOs and NBFIs are expected to lend to the poorest households without collateral and so have higher premium for risk. Moreover, these deprived clients borrow in small amounts and therefore also have greater unit administration costs, not to mention the cost of foreign and vehicles employment by NGOs in particular. Besides, these underprivileged borrowers may be more concerned with access to capital rather than "cheap" loans. They therefore could be unresponsive to price increases, permitting those MFIs which purport to serve them to offer credit at considerably high interest rates. What is more, the absence of effective regulation and public scrutiny may have allowed such institutions to charge interest rates which are significantly higher than their average costs, compared with microfinance banks which often attract intense media attention and possible censure. Thus, decisions on whether sustainable NGOs and NBFIs are meeting their professed social obligations must be based on the presumption that any subsequent relatively high profits are channelled into initiatives which ultimately reduce average interest charges.

The group of credit unions charging the lowest average rates at 23.01 percent a year, compared with the 29.94 percent for rural banks and 31.17 percent for other types of microbanks. The comparatively low interest rates levied by credit unions are to be expected. These are not-for-profit cooperative financial institutions owned by their members who pool their money to provide loans and other financial services. This should reduce the need to raise finance from more expensive external sources, leading to a lower cost of basic finance and the interest rate therefrom. Then too, the profits from other services, notably from marketing members' inputs and outputs, may be used to cross-subsidize interest rates and extract repayment of loans. Besides, the cooperative structure of credit unions is designed to ensure fair dealing. Consequently, interest rates which are deemed to be "excessively" high are unlikely to be countenanced by members. Additionally, members and borrowers of credit unions are often the same people and so are jointly responsible for the administration and repayment of loans. This sense of collective liability doubtless leads to lower default rates and management costs with a consequent decline in interest rates. Also, credit unions are often local institutions and, as shown in Figure 1B, are mostly mature small scale operations. They are therefore more likely to offer more personalised customer services to users and to know more about the creditworthiness of their borrowers.

Another discernible pattern across the MFIs in Figures 2A and 2B is the low interest rate observed for rural banks by comparison to their other bank counterparts. Normally one would expect that the lack of competition in village micro-credit markets would enable banks there to charge interest rates that might look abnormally high when compared with those of other bank providers. The implication is that rural microbanks, like traditional village moneylenders, have acquired a comparative advantage in drawing up credit contracts which help mitigate those adverse selection and moral hazard problems that have discouraged urban providers from lending to poor borrowers. Further, it is more likely that the majority of rural banks are government-sponsored agricultural lending agencies, often with a cap on their rates, although it has to be admitted that government banks often suffer from high default rates as borrowers see no need to repay a public institution (Nwachukwu, 2013b).

A further disaggregation by age and size of operation in Figures 2A and 2B respectively indicates that interest rates tend to decline with the age and scale of an average financially sustainable MFI regardless of its legal intermediation status. Standard economic theory would lead us to suppose that reductions in costs driven by experience, learning by doing, economies of scale and growing competition are responsible for the lower interest rates observed for mature and large scale MFIs. So for established institutions with more than eight years' experience, microcredit interest rates dropped to an average of 30.89 percent a year, representing a fall of 1.97 percentage point from the overall sample average of 32.86 percent of gross loan portfolios. In terms of scale, Figure 2B implies that the drop in interest rates accompanying increases in the value of gross loan portfolios outstanding was larger than the fall in rates arising from variations in the age of an MFI. For example, for the large-scale MIX-MFI, the mean interest rate was 28.83 percent per annum vis-à-vis the 30.89 percent observed for a representative mature microlender; a difference of 2.06 percentage points. Once again, separation by type of MFI suggests that the implied inverse relationship between age and scale economies against interest rates is more pronounced across our NBFI sub-sample.

Generally speaking, two key issues emerge from our summary statistics in this section. *First,* there is an indication that a quicker way to lower microcredit rates is for providers, especially those in the newly established non-bank financial sector, to pay closer attention to those costs which tend to fall with the scale of lending operations. Such scale economies arising from lending to more clients and/or by increasing the value, duration and range of borrowing facilities offered to existing clients with a good credit history would make the provision of microcredit more efficient. *Second*, the effect of age and scale economies appears to be closely correlated, especially for the NBFI category. This outcome is almost certainly a consequence of the fact that it takes time to understand and exploit opportunities for cost efficiencies embodied in large scale microcredit operations. The implication is that an interaction term which combines MFI's age and scale of lending over time should be included in any empirical study which claims to investigate the effect of the two variables on interest charges. The regression model which we employ in this study to analyse how age and scale economies affect annual interest rates of selected operationally self-sufficient MFIs in the MIX developing country database is outlined in the next section.

2. Empirical Model and Hypotheses

The argument in this section is carried out under the following headings: (i) model specification, (ii) variables of interest, (iii) control variables and expected relationships and (iv) empirical estimation method.

2.1: Model Specification

This paper investigates how financially self-sufficient microfinance institutions may influence their interest revenue through: (i) the adoption of traditional banking practices, (ii) knowledge acquired by serving clients over time and (iii) scale economies achieved by serving a growing number of borrowers and/or by increasing the average size and duration of a loan. The model which we use to capture the influence of these three characteristics of MFIs on interest rates can be expressed in terms of the following regression equation.

$$\begin{aligned} Log(YLD_{it}) = \beta_0 + \beta_1(MATURE_{it}) + \beta_2(MSCALE_{it}) + \beta_3(LSCALE_{it}) \\ + \beta_4(MICROBANK_{it}) + \beta_5(MATURE_{it} * MSCALE_{it}) \\ + \beta_6(MATURE_{it} * LSCALE_{it}) \\ + \beta_7(MATURE_{it} * MSCALE_{it} * LSCALE_{it} * MICROBANK_{it}) + \pi_{zj}(Z_{jt}) \\ + \alpha_i + \varepsilon_{it} \ldots\ldots (Eqn\ 1) \end{aligned}$$

The variable YLD was defined previously in section 1.3 as the gross loan portfolio yield on microloans.

2.2: Variables of Interest

The independent variables of particular interest comprised: (i) the entry MATURE is a dichotomous dummy variable indicating the number of years the institution has been operating. Following the classification by MIX analysts, this variable takes a value 0 if the institution has less than eight years of operation and 1 otherwise. The decision to merge the NEW (i.e., age < 5 years) and the YOUNG (i.e., age between 5 and 8 years) variables to create a "NEW-YOUNG" dummy series follows from a lack of sufficient observations for each individual category in our dataset. (ii) The notations for MSCALE and LSCALE are dummy variables for medium and large-scale institutions which are entered in our specification independently in that order.(iii) The term MICROBANK is a dummy variable for microfinance banks which takes a value of 1 if the MFI is classified as a "rural bank" or "bank" and 0 for our three other types of institutions —NGOs, NBFIs and credit unions or cooperative societies. This sub-sample of institutions which do not have an authorised license to carry out conventional banking activities is collectively hereafter referred to as "NON-BANK-MFIs". The decision not to include separate dummies for each type of MFI (rural versus other types of bank) in the equation was based on the fact that there were too few observations for them. The dummies for NEW-YOUNG, SMALL-SCALE and NON-BANKMFIs are excluded from the regression to avoid an exact linear association between the three dummies and the intercept term. This means that the constant term β_0 represents the annual average interest charge for these omitted classes of sustainable MFIs. Our null hypothesis is that the differential intercept coefficients $\beta_1, \beta_2\ and\ \beta_3$ are less than zero. These parameters capture the dissimilarity in the annual average interest rates between the respective age and scale measurement and the corresponding new-young and small-scale microcredit providers.

The coefficient β_4 shows how the annual average interest income varies across MFIs by the nature of their accredited activities. We propose that the coefficient β_4 will have a negative sign. This follows from the expectation that microfinance banks are more cost-efficient than the other types of MFIs, presumably because they are in more direct competition with conventional commercial banks. We hypothesise that microbanks are relatively more innovative than our other types of MFIs, both in terms of their sources of funds and in their types and methods of delivery of financial products. However, Christen *et al* (2003) suggested that the coefficient β_4 may have a positive sign. They remarked that the extra costs to microfinance banks of complying with formalisation and prudential regulations was as much as five percent of assets in the first year of transition, declining to around one percent in subsequent years. Sustainable MFIs will ultimately pass these additional regulatory costs onto their borrowers in the form of higher interest rates.

As MFIs get older, they normally attempt to increase their customer base and also make progressively larger-sized loans to their existing clients with successful businesses. To investigate the significance of the implied combined effects on interest rates of age, scale economies and organisational charter, we include simultaneously in our regression model *three* interaction dummy variables. The combinations (MATURE*MSCALE) and (MATURE*LSCALE) are created by multiplying the dummies for mature with medium and large scale MFIs in that order. It is anticipated that the slope differential coefficients $\beta_5\ and\ \beta_6$ will have negative signs to reflect the additional productivity gains enjoyed by well-established MFIs that exploit scale economies by comparison with their new-young and small-scale enterprises, irrespective of license type.

We differentiate between interest charges borne by borrowers from mature-medium-large scale microbanks versus NEW-YOUNG microbanks, by introducing an interaction term (MATURE*MSCALE*LSCALE*MICROBANK). We predict that the differential slope β_7

is negative in recognition of the fact that mature-medium-large microbanks are more likely to have improved governance and internal controls and to be better at coping with the risk and cost associated with regulation and its supervision. Such should instil confidence in external finance providers and depositors, leading to a lower cost of funding with a corresponding fall in interest charges. Also, it is expected that established large microbanks have acquired the experience and scale economies needed to manage and price microcredit risk better. They should therefore have lower cost structures with an associated decline in their interest rates.

2.3: Control Variables and Expected Relationships

The symbol Z_j in equation 2 is a vector comprising the set of control variables drawn from a pool of potential determinants theoretically or empirically linked to changes in interest rates on microloans in the microfinance literature. Generally speaking, discussions by Christen (2000), Woller and Schreiner (2010) indicated that several empirical studies which use the MBB dataset have consistently found the following ten institutional characteristics to be important drivers of interest rates on microbanking loans aside from the age and scale variables described in section 2.2. These ten conditioning variables have been added simultaneously to our extended regression in equation 2.

$$\begin{aligned} Log(YLD_{it}) = \beta_0 &+ B_1(MATURE_{it}) + \beta_2(MSCALE_{it}) + \beta_3(LSCALE_{it}) \\ &+ \beta_4(MICROBANK_{it}) + \beta_5(MATURE_{it} * MSCALE_{it}) \\ &+ \beta_6(MATURE_{it} * LSCALE_{it}) \\ &+ \beta_7(MATURE_{it} * MSCALE_{it} * LSCALE_{it} \\ &* MICROBANK_{it}) + \pi_1 Log(FELR_{it}) + \pi_2 Log(OPER_{it}) + \pi_3(PFLR_{it}) \\ &+ \pi_4 Log(PROFTR_{it}) + \pi_5 Log(PAR30_{it}) + \pi_6 Log(WBR_{it}) \\ &+ \pi_7 Log(BPSM_{it}) + \pi_8 Log(1 + ECAR_{it}) + \pi_9 Log(ALPBP_{it}) \\ &+ \pi_{10} Log(ALPBPSQ_{it}) + \alpha_i + \tau_t + \varepsilon_{it} \dots\dots (Eqn\ 2) \end{aligned}$$

The ***first*** information-conditioning variable is FELR, measured as the ratio of the cost of funds to gross loan portfolio for an MFI. The coefficient π_1 captures the effect on microcredit rates of policies affecting the terms and the amount providers pay for their funds. A tightening in the terms, conditions and diversity of funding sources would raise the average finance-expense ratio, causing a rise in interest rates. This implies a positive π_1 coefficient.

The ***second*** variable, OPER, is the ratio of operating expenses to gross loan portfolio. This is used to proxy the efficiency with which an MFI delivers its loans to its clients. We would expect that sustainable MFIs with higher operating cost structures would charge higher interest rates. This suggests that the coefficient π_2 will have a positive sign. Nevertheless, Campion *et al* (2010) and Armendáriz and Morduch (2010) observed that the imposition of interest rate caps by some developing country governments, such as in Ecuador, may push profit-orientated MFIs to lower costs by targeting wealthier borrowers who borrow larger amounts and for longer periods. Such would result in an inverse relationship between average portfolio yield and operating costs. Therefore, we cannot conclude beforehand what the sign on the coefficient π_2 will be.

The interest rate consequences of the money set aside by MFIs to cover potential loan defaults are captured by the ***third*** conditioning variable PLFR. It is hypothesised that microcredit interest rates will be higher when provisions for loan impairment rise. This is because increases in the level of provisioning represent an expected loss of revenue and opportunities forgone for the lender (Cotler and Almazan, 2013). Thus, a positive sign is anticipated for the $\pi_3$coefficient.

The ***fourth*** control variable, PROFTR, is profit measured as net operating income relative to gross loan portfolio. It is expected that MFIs which wish to increase profit per unit of loans would have to raise their lending interest rates. This indicates a positive correlationπ_4 between portfolio yield and profit margin. But Campion *et al* (2010) pointed out that profitable MFIs are more likely to invest in initiatives needed to improve the quality and range of services provided to both existing and as yet un-served clients. Any subsequent reduction in costs should contribute to lowering interest rates in the long-term, leading to a negative π_4 coefficient. Besides, those MFIs which raise profit targets are normally subjected to public pressure to cut their microcredit interest rates. Fear of such concerted civic protests has resulted in a fall in interest rates in the past. Consequently, the sign on the coefficient π_4 cannot be ascertained *a priori.*

The quality of an institution's loan portfolio is measured by our ***fifth*** control variablePAR30. This is the proportion of an MFI's loans that have one or more principal instalments unpaid for more than thirty days past their due date. Thus, a rise in this variable indicates a deterioration in the quality of an MFI's loan portfolio. We theorise that MFIs with poor portfolio quality are unable to contain their costs, leading to higher interest rates. This implies a positive sign on the coefficient π_5.

The ***sixth*** variable in our conditioning set is, WBR. This represents the proportion of women borrowers which supposedly captures the depth of outreach to the underprivileged population by an MFI (Woller and Schreiner, 2002). Evidence shows that socially-oriented MFIs tend to serve a greater fraction of females than males, primarily to overcome cultural biases against females (Cull *et al*, 2007; Campion *et al,* 2010). Further, women are normally targeted by programmes with pro-poor goals because women are more likely to spend earnings from their microbusiness on their family's welfare, including their children's education, nutrition and health (ILO, 2008; Campion*et al,* 2010). However, women also tend to live in rural areas and take smaller loans compared to men. This drives up the operating costs of any lender who targets them. The implication of such extra costs of serving an increasing share of female borrowers is represented by a potential positive sign on the coefficientπ_6. On the other hand, observers have noted that female borrowers are more likely to repay their loans on time which lowers loan-loss provisions. This last argument lends support to the hypothesis that MFIs which serve a higher percentage of women are more inclined to charge lower interest rates. It seems that the evidence from the literature on the relationship between interest rates and the percentage of women clients is inconclusive (Pitt and Khandker, 1998, Brau and Woller, 2004).

The ***seventh*** conditioning variable BPSM is the ratio of borrowers to staff members. It is included to approximate the relationship between interest charges and the effectiveness with which an MFI manages its human resources. A typical client for an MFI tends to be uneducated and to be poor at keeping records of business earnings and repayment history. MFI staff must spend a lot of time in the screening and monitoring of prospective clients and their businesses, as well as in helping customers to understand the features of the institution's financial products, evaluating the feasibility of the project for which they want to borrow and completing loan application forms. A rise in the BPSM variable may be construed as a sign that the MFI is succeeding in dealing with these borrower deficiencies without a corresponding increase in the number of employees. Any consequent reduction in personnel costs per unit loaned should be correlated with a fall in annual average interest charges. A negative sign is therefore anticipated for the coefficientπ_7. Alternatively, more borrowers per staff member may result in a cost-raising deterioration in the quality of services and the supervision of loans. Olomola (2001) and Nwachukwu (2013b) pointed out that an increase in the BPSM ratio may be a sign that the institution is cutting down on the number of employees. Any subsequent reduction in the number of staff for site visits, loan monitoring and recovery can raise the default rate and related interest charges. The foregoing implies that the effect on interest rates of the number borrowers relative to staff members as represented by the sign on the coefficient $\pi_7$may be either positive or negative depending on the level of education and creditworthiness of the borrowers.

The ***eighth*** *control* variable in our equation two is ECAR which is represented as the ratio of equity capital to total assets. Existing research on the capital structure of MFIs is posited within the context of the life cycle theory of institutional development (Farrington and Abrams, 2002; Fehr & Hishigsuren, 2004; Helms, 2006; and Bogan *et al*, 2007). According to the life cycle approach, funding patterns are linked to the stage of development of the MFI. Traditional equity finance, as opposed to grants-in-aid and concessional loans from donors, comprise the majority of the funding in the later stages of an organization. In this mature phase, many MFIs are large scale enterprises and will have established internal control and management structures needed for complying with prudential and market regulations. They are therefore more likely to have obtained an investment grade rating which should help them attract more equity finance from private investors. Thus, a rise in the equity capital ratio may be regarded as an indication that the MFI is a mature large scale organisation and requires access to long-term equity to further expand and/or improve the range and quality of its services. A significant positive correlation coefficient π_8 would indicate that a typical MFI experienced a considerable increase in the operating costs of meeting the regulatory obligations, including the expansion of physical and intellectual capital to handle the additional legal and reporting demands (Sinkey and Carter, 2000; Christen *et al*, 2003). Such extra costs will be passed on to customers through higher interest rates. A negative relationship, on the other hand, suggests that, on average, our MFIs used the proceeds from newly issued equity capital to recapitalise by repurchasing outstanding debt in order to meet a required capital adequacy ratio regulation. Any subsequent reduction in the likelihood of bankruptcy should lower the cost of funding with an associated decline in interest rates. This means that the sign on the π_8 may not be confirmed beforehand.

The ***ninth*** variable, ALPBP, is the average loan size per borrower relative to the per capita GNI of the country in which the institution is located. The smaller the average loan size, the larger the probable fraction of the poorest borrowers served by the institution. In fact, information from MIX indicates that socially-oriented MFIs which cater for the financial needs of deprived borrowers at the low-end of the credit market tend to make small-sized loans of less than 20 percent of the per capita GNI of the country in which they operate. But because each loan application goes through a similar cost of vetting process, we expect that total operating costs with their associated interest rates will be higher for MFIs with more outstanding small loans than their counterparts with fewer, larger credits. Thus, a positive correlation coefficient π_9 could be expected if those institutions most focused on a social mission charged higher interest rates to offset the greater unit transaction costs of providing an increased number of small average loan amounts to disadvantaged borrowers.

The ***final*** variable in our conditioning set is ALPBPSQ. This is the square of an average loan-size per borrower per capita GNI used as a proxy for an institution's outreach to the wealthier borrowers capable of servicing larger loan sizes. The decision to include this quadratic term follows from the observation by Armendáriz and Morduch (2010) that the greatest challenge facing most MFIs is how to recompense for the high fixed cost of lending in small amounts. Cotler and Almazan(2013) noted that most financially self-sustaining MFIs, especially those which operate in countries where rates are capped, are tempted to deal with this concern by re-orientating their services towards wealthier borrowers with the capacity to service larger loans. Evidence shows that the consequent lower costs are passed on to borrowers in the form of lower interest charges. Further, MFIs that make larger loans are more likely to want their borrowers to pledge collateral which, in turn, lowers interest rates. Moreover, if larger loans are made progressively to the more experienced and educated class of borrowers with successful businesses, then the operational costs and the risk of default should decline and with them interest rates. We would therefore expect to find a negative correlation coefficient π_{10} between interest rates and the squared-average loan size variable.

The symbol α_i is a dummy variable representing the effects of those unobserved characteristics which are unique to a particular ith MFI and which do not vary over time t. These institution-specific dummies are treated as either fixed or random parameters depending on the outcome of a test proposed by Hausman (1978)[5]. The symbol τ_t is a dummy variable for time. These time indices are also treated as fixed or random in order to capture the dynamic changes in the rate of interest over our six years of study. The notation ε_{it} is the white noise disturbance term with an expected value of zero.

[5] The results of the Hausman test for fixed versus random model is not reported here in order to conserve space.

2.4: Empirical Estimation Method

To test the validity of the above-mentioned hypotheses on the relationship between nominal interest income and its key determinants, we employ two estimation techniques. The *first* is a basic correlation analysis which considers the degree of linear association between interest rates and each individual control variable. We estimate the Kendall tau(τ) rank correlation coefficient which deals with the problem of outlying observations and ties in the orderings of data. The *second* method is a multivariate regression model in which the dependent and explanatory variables are presented in equation 2 above.

The single expression in equation 2 assumes that all the right-hand-side (RHS) variables are exogenous in the sense that their values are determined outside the microcredit pricing system. But representations in Section 1 imply that this is a rather simplistic assumption. Besides, arguments in previous empirical studies by Rosenberg (2007), Hudon (2007), Kinsley (2008), Cull *et al* (2009),Campion (2010) and Cull*et al* (2011) suggest that there is probably a causal link between interest income and the institutional characteristics contained in our information conditioning set. What is more, the result of a Hausman test for exogeneity indicates that all the control variables described in section 2.3 are indeed jointly determined within our regression model and so must be treated as endogenous variables[6]. This is to be expected as these variables represent the institutional features which managers seek to influence in order to achieve optimal pricing for their niche market. Thus, the treatment of these variables as exogenous in a number of articles, including the influential paper by Cull *et al* (2007) which uses an Ordinary Least Squares estimator, is invalid.

A potential solution for endogenous regressors would be to run a distributed lag model in which the current value of our dependent variable (YLD_{it}) depends on the previous values of the explanatory variables in our conditional set(Z_{jt-1}). But, as explained by Brooks (2008), the use of lagged variables in a regression violates the classical linear regression model assumption that explanatory variables are non-stochastic. Then too, most functional forms with lagged variables are over-identified and therefore could produce biased coefficient estimates. Besides, the coefficient estimates of such distributed lag regressions are difficult to interpret and may not accurately reflect the financial theory which originally motivated the empirical analysis. One technique frequently used for the estimation of systems

[6] Once again, for the sake of brevity, the results of the Hausman test for exogeneity are not reported here, but are available on request from the author.

of equations when contemporaneous variables are specified as endogenous is the Two Stage Least Squares (2SLS).The perennial problem of choosing valid instruments from freely available data is resolved by employing two period lagged values of all the variables in our conditioning set. Ideally, the restrictions placed on the choice of appropriate instruments and lag lengths should be informed by financial and economic theories. But often these theories are at best vague or at worst non-existent. As a result, searching for exogenous variables to be used as instruments in simultaneous specifications has been carried out in an *ad hoc* manner. It has been argued that the measurement error associated with such an unplanned selection of external instruments could be minimised by using the VAR approach (Sims, 1980; McNees, 1986). With respect to lag lengths, our priority was to include as many cross-sections of MFIs as possible in our regression analysis while ensuring that each of these institutions has data for at least three out of our six years.

We recognise that the components of our regression equation which are expressed at natural logarithm levels may contain unit roots and so should have been differenced to induce stationarity. Nonetheless, the resolution to run the regression at level follows from the fact that the objective of this article is to examine the relationship between interest rates and key MFI characteristics. Differencing would have resulted in a loss of any long-run information on the correlation between these variables. In any event, the influence of non-stationarity on the behaviour and properties of data is less pronounced for our panel dataset which comprises a large cross section of 1232 operationally self-sufficient MFIs with a relatively short-term time period of six years. Besides, the transformation of all the regressors into natural logarithm series helps to lessen the problem of spurious regression by ensuring that the variables follow a linear trend and are integrated (Asteriou and Hall, 2007, Brooks, 2008).

The problem of multicollinearity is a key concern in multiple regression models. But, results in Appendix Table 2 indicate that the degree of interdependence between our explanatory variables is relatively low at under 0.5. Indeed, multicollinearity is rarely a problem in dynamic panels which pool a large cross-section of institutions from different countries over a relatively short-time period. Such a data arrangement reduces the likelihood that the same common trend will be prevalent in the regressors in the model specification.

3. Estimation Results

This section presents our empirical results under (i) correlation and (ii) regression analysis.

3.1: Correlation Analysis

Appendix Table 2 reports the contemporaneous pairwise correlation matrix of our selected control variables based on the Kendall tau-b matrix. As expected, the positive linear association between microcredit interest rates and operating expenses is the strongest. This is consistent with the observation by Rosenberg *et.al* (2009) that such costs make up the bulk of interest charges. The relatively high correlation coefficient of 0.49 indicates that the provision of microloans is a high-cost activity. As a business model, the greatest challenge is to lower operating expenses both in terms of those for personnel and for administration. Other institutional characteristics with estimated positive correlation coefficients include cost of funding, loan-loss provision, profit margins, fraction of women borrowers and the ratio of equity to total assets.

Contrary to expectation, the sign on the coefficient for the average loan balance per capita GNI is negative. We may therefore infer that the majority of our financially self-sufficient MFIs have not crossed the cut-off point at which potential gains from larger loans are lost. This phenomenon may be explained by the fact that many profitable MFIs now employ the so-called "credit–plus" approach. This involves the provision of additional business development services, including health, consultancy, marketing and record keeping instructions to borrowers in order to enhance the size and productivity of the loans provided.

Surprisingly, interest income is inversely correlated with the proportion of loans that have passed their due date by thirty days. This unexpected outcome is consistent with the allegation that the LPAR30 series is a conservative measure of portfolio quality (Armendáriz and Morduch, 2010). The inclusion of all principal instalments unpaid after a month of their expected date ignores the benefits of missed balances that are eventually repaid. Then too, the worsening in the risk of default as signalled by a rise in this variable does not account for the fact that MFIs have a good knowledge of their customers and their business environment. They are therefore able to discern when non-repayment is due to genuine hardship, rather than shirking. A significant negative coefficient for the LPAR30 variable suggests that when loan default is proven to be due to a real deterioration in the financial circumstances of their clients, our typical MFI may have elected to restructure or reschedule the terms of lending either through a cut in interest rate or an extension of the repayment period. The decision not to punish those honest clients who have fallen on hard times with higher rate charges is probably in recognition of the original social mission of the microfinance movement.

Another unexpected result in Appendix Table 2 is the relatively low positive correlation of 0.25 between loss provisions (LPFLR) and the percentage of loans at risk of default after 30 days (LPAR30). There is an inference that MFIs are not putting aside enough money to deal with the difficulties which may emerge with missed instalments. Besides, as noted by Armendáriz and Morduch (2010), MFIs may not consider information from the 30-day PAR when deciding on the ratio of loss provision. They may rather use the 60-day or 90-day ratios, presumably because of the belief that missed repayments are eventually recovered months after their due date. Nevertheless, the extent to which the pairwise correlations in Column 1 are biased by the simultaneous exclusion of the other MFI characteristics used as explanatory variables in our multivariate regression in equation 2 will be explored in the next section.

3.2: Regression Analysis

The outcomes of our estimation for equations 1 and 2 using the 2SLS method are presented in Columns 1 and 2 of Appendix Table 3 in that order. The regression in Column 2 highlights how the sign, size and statistical significance of the coefficients on our key variables of interest —age, scale economies and microbanking dummies— vary with the concurrent inclusion of our choice of conditioning variables. It is noteworthy that the regression in Column 2, has the highest adjusted R-squared and F-statistic. Besides a Durbin-Watson statistic of 2.04 indicates a lack of first-order serial correlation in the disturbance terms. Consequently, much of our argument here is based on the estimates from the regression presented in Column 2. The discussion is organised under: (i) age, scale and microcredit interest rates, (ii) microbanking and (iii) other MFI characteristics

3.2.1. Age, scale and microcredit interest rates: The results in Appendix Table 3 indicate that the relationship between age, economies of scale and interest rates is sensitive to our set of conditioning variables simultaneously included in the regression model. For example, we reported in Column 1, that, on average, a mature MFI with more than eight years of experience has a marginally higher average portfolio yield than new-young institutions, even if this finding is weak from a statistical viewpoint. In Column 2, the coefficient on the age variable (i.e., MATURE) reverted to the expected negative sign, although the MATURE dummy is still statistically insignificant. Most likely, this negative correlation is capturing the cost-reducing effect of a movement along a learning curve over time. As noted by Cull *et al* (2007) and Campion *et al* (2010), the number of years of an MFI's operation is a proxy for knowledge. Established MFIs are more likely to have accurate information on the credit risk profile of their borrowers. They would therefore be able to adjust their lending practices, including the amount and terms of borrowing to suit the peculiar features of each customer.

With respect to economies of scale, the positive coefficients on the MSCALE and LSCALE dummies are persistent across the two regressions, although statistically insignificant in the model in Column 2. Nonetheless, the results suggest that larger MFIs have higher average interest rates than their smaller rivals; keeping the average values of all other conditioning variables constant. This unexpected outcome is presumably related to the observation by Gonzales (2007), Rosenberg *et al* (2009) and Campion *et al* (2010) that MFIs are unlikely to experience any additional reductions in their costs from scale economies once they have grown beyond a certain number of borrowers. Then too, this anomaly may be because of the self-reporting bias in the MIX data underlying our regression. As we pointed out in Section 1.1, the MIX data is unrepresentative of the microfinance landscape in the developing world in the sense that it likely comprises the more successful, larger-end of the distribution of MFIs.

Given the probable bias in the size of the MFIs that comprise our sample, we investigate the extent to which the age of operation could also be an influential factor on the relationship between scale and interest rates. The significant negative sign of the coefficient on the interaction terms MATURE*MSCALE and MATURE*LSCALE in our basic regression in Column 1 is consistent with the null hypothesis in Section 2.1, even if the coefficients were later found to be insignificantly different from zero at the conventional five percent level in the extended regression in Column 2. Nevertheless, we may infer that well-established medium-large scale MFIs have slightly lower annual average interest rates than new-young small ones. Older MFIs have learned how to structure their loan sizes and pricing policy to the credit history as well as the income-expenditure stream of their clientele. This has allowed our mature- medium-large institutions to marginally extend the cut-off point beyond which gains from economies of scale are predicted to dissipate.

3.2.2. Microbanking and microcredit interest rates: The significant positive coefficient of 0.30 on the MICROBANK dummy in Column 2 conforms with the assertion by Christen *et.al* (2003) that the extra costs of becoming a formal regulated microbank are passed on to borrowers through a higher average portfolio yield than our unregulated non-bank MFIs. This statement is further supported by the positive coefficient of our interaction variable MATURE*MSCALE*LSCALE*MICROBANK, even if this is insignificantly different from zero. It appears that established medium-large microbanks charge slightly higher interest rates than their new-young counterparts, probably because they face greater scrutiny with associated regulatory and supervisory costs. Also, as we said earlier, mature microbanks are in more direct competition with much larger traditional commercial banks. Thus, the positive coefficient here may be linked to the effect of competition on outreach. For example, as competition intensifies, microbanks may be pushed to establish new branches in poorer neighbourhoods and in more remote villages in search of new customers using existing technology and lending approaches. It seems that such drives into new markets are related to higher personnel and administrative costs and possibly an increase in non-repayment rates. Nonetheless, we may infer from the statistically insignificant positive coefficients on the microbanking interaction terms that only a few well-established large microbanks were able to adequately raise their interest rates to cover the extra cost of this transformation.

3.2.3. Other MFI characteristics and microcredit interest rates: *A*nalysis of our regression model in Column 2 identified five out of our ten control variables as statistically significant drivers of interest rates at the conventional five-percent level.

The significantly positive correlation coefficients which were estimated for the two cost components of interest rates —cost of funds (LFELR) and operating cost (LOPELR), are consistent with our prediction.

The positive sign of the net profit variable (LPRFTLR) is statistically significant. Contrary to the claim by Rosenberg *et.al* (2009), the relatively large size of this coefficient suggests that the quest for profits is the most important reason for the differences in the lending interest rates among financially self-sufficient MFIs. A one percentage point increase in anticipated net profit per unit of loan portfolio will raise nominal portfolio yield by 0.14

percent, after accounting for the impact of the other regressors in the equation specifications. The results also show that the size of the coefficients on the profit variable is nearly double that for each of our unit cost components. This indicates that sustainable MFIs, in their search for profit maximisation, raise interest rates by almost twice that of associated increases in the total unit cost of lending. Such may be taken as evidence of "*mission drift*" unless we presume that the higher profit is re-invested in the expansion of outreach to underserved poorer communities.

The entries in Column 2 indicate that the borrowers per staff ratio (LBPSR) is the only other control variable whose relationship with interest income is statistically significantly at the five percent level. Most notably, we found that contrary to the pecking order capital structure theory, interest rates charged by MFIs that use the more expensive external equity capital to finance larger loans is comparable to those charged by their counterparts that rely on internally generated funds such as retained profit. In line with this finding, we may therefore surmise that there is little or no risk that microcredit interest rates will be raised as more and more MFIs shift their funding structures towards purely commercial investment in the wake of the on-going budgetary problems faced by western donor governments.

Conclusions and Policy Recommendations

The objective of this paper has been to discover how interest rates charged by financially self-sufficient MFIs respond to: (i) knowledge which comes from the age of an institution,(ii) scale economies and (iii) changes in an institution's charter through the adoption of conventional banking practices. It focuses on annual time-series panel data for1232 operationally self-sufficient MFIs from 107 countries across six developing regions from 2005 to 2010. Using basic descriptive statistics, pairwise correlation analysis and a two-stage least squares regression estimator, we uncovered *three* key discernible patterns in the behaviour of microcredit interest rates. These underlying trends with related policies may be summarised as follows:

First, the insignificantly negative coefficient on the institutional age variable indicates that older MFIs with more than eight years' experience have acquired a slender comparative advantage from possessing historical records of the income and expenditure streams of their clients. Such could have allowed them to make progressively larger loan sizes to repeating customers at comparatively lower rates than their new-younger rivals. With respect to organisational scale variable, we found a positively insignificant coefficient. We may postulate that the cost competitive advantage enjoyed by medium and large institutions vanishes after a certain cut-off point. However, the negative coefficient on the age-scale interaction term suggests that a handful of well-established large MFIs have succeeded in slightly raising this threshold beyond which gains from scale economies will dissolve.

An important public policy initiative for reducing the price of lending which may be adduced from these results are that governments should encourage the older and more efficient MFIs to increase institutional scale by merging and/or acquiring new-young MFIs. In addition, the authorities should promote campaigns in the media and within the institutions themselves to disseminate lessons learned by mature providers. Furthermore, MFIs with less than eight years of experience can mitigate their cost disadvantages by investing in market surveys to gather client opinion on various aspects of the services which they have received (Campion *et al*, 2010). Then too, staff of nascent MFIs in particular may be trained on how to use new technologies, such as credit scoring to collect, record and use information on client credit risk profiles to determine the charge on, and amount of loan extended to each borrower. These initiatives should help new-young MFIs to leapfrog the difficulties associated with the early stages of a learning curve.

Second, the robustness of the positive sign of the MICROBANK dummy suggests that the shift from socially-orientated to fully regulated micro-banking status typically leads to higher interest rates for customers of banks of all ages and scales. The inference is that such a transformation imposes extra costs on microbanks and that these expenses are eventually passed onto their customers.

Broadly speaking, our findings indicate that policy makers could lower the average interest rates for microbanks by reforming the prudential regulatory framework which this class of MFI is required to follow. Ideally, an effective regulatory structure for monitoring the activities of microbanks should take into account the differences in the size of their collateralised loan portfolios and client risk profiles vis-à-vis that of traditional commercial banks which are often bigger and employ more innovative technologies. Such a revision should ensure that compliance is not so burdensome and expensive that it leads to higher interest rates and/or limits the number of available microbanks which provide financial services to the poorest population. Then too, a government could offer financial assistance and technical advice to microbanks to facilitate their transformation into regulated entities.

Microfinance banks themselves may help mitigate the adverse effect of regulatory costs by expanding the range of products offered to clients in different target markets. Cross-subsidization of expenses from various market segments and products could be used to lower interest rates to the poorest clients (Armendáriz and Szafarz, 2009).Raising staff productivity is another practice which may help lower the cost of transition to formal microbanking. Policy initiatives which link incentive systems with staff bonuses and training needs to recognisable performance targets, such as the collection of savings deposits and loan repayments from clients, should help improve staff morale and efficiency. Besides, microbanks might invest in modern technologies such as internet and telephone banking in order to lower their operating costs per borrower. Microbanks can further lower transaction costs by using mobile vans to reach more low-income clients in remote rural areas rather than setting up branches there. Moreover, hiring local officers with a specialised knowledge of the culture and locality in which borrowers live and work should help improve ease of access to, and communication with borrowers, but this will, of course, be done at a cost.

Third,the pursuit of higher profit goals by sustainable MFIs, regardless of legal status, raises interest rates by almost double any corresponding upturn in the unit cost of lending. Such may be taken as evidence of "*mission drift*", indicating that profit-driven shareholders are using their involvement to exert pressure on the pricing policy of MFIs.

The fear that financially self-sufficient MFIs are deviating from their original mission may be reduced by policies which encourage profit earned to be re-invested in the institution itself rather than distributed to shareholders or management. Such policy actions may include an increase in taxes levied on profits which are not re-invested in welfare maximisation initiatives. Additionally, concerns about excessive profit targets could be dealt with by implementing policies which foster competition in the microfinance sector. These initiatives may involve the setting up of a regulator which overseas accountability and transparency in the recording and timely publication of the audited accounts of MFIs, dividend payments and the names of their recipients. Also, the creation of independent price comparison websites and agencies which rank the performance of MFIs on the core principles of investor and borrower protection should increase the confidence of depositors, shareholders and other providers of funding to MFIs. Then too, governments should try to set-up an identity system for its citizens together with associated credit rating bureaus to facilitate the collection and comparison of the profile of borrowers. This should provide incentives for participation in the provision on microloans by the more socially-minded MFIs and lower interest rates. Further, the authorities could take out advertisements in national newspapers, on television, billboards, Facebook, Twitter and the other social media to encourage borrowers to seek out alternative lenders and to switch to cheaper providers. Besides, an aggressive campaign in the popular media to name and shame the directors and shareholders of MFIs that charge "excessively" high interest rates may force them to consider their pricing policy to ensure that it is in compliance with their stated social mission.

Arguments in this paper have shown that promoting competition and encouraging the adoption of new technologies are important actions which governments could take to reduce the interest rate charged by microfinance banks in particular. However, carrying out empirical testing on the effect on interest income of such interactions between intensity of competition and type of lending technologies is very difficult because of a lack of data at local market levels for individual MFIs over time from widely available databases such as MIX. Such must be the subject of further research which uses information collected from questionnaires, field visits and interviews with senior management of formalised microbanks to assess how they adjust their interest rates to include the extra regulatory and supervision costs. It would also attempt to quantify the effectiveness of the various innovative approaches used by microbanks to mitigate the consequences of additional transformation expenses for their clients at different income levels and locations.

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Appendix Table 1: Mean of Selected Sustainable MFI Characteristics used in the Study

Items		*Credit Unions*	*NBFIs*	*NGOs*	*Rural Banks*	*Other Banks*	*MIX-MFIs*
1.	***Yield on GLP (nominal, %)***						
a	New	31.25	41.30	37.77	39.95	38.00	39.10
b	Young	27.88	41.44	37.82	35.65	33.91	37.78
c	Mature	21.45	33.33	33.40	29.21	29.37	30.89
d	Small scale	25.28	43.10	37.80	34.46	46.81	36.94
e	Medium scale	23.73	38.99	33.43	28.41	43.33	33.66
f	Large scale	18.85	31.27	30.10	26.66	28.08	28.83
g	All MFI sample	23.01	36.58	34.31	29.94	31.17	32.86
2	***Financial expense (% GLP)***						
a	New	6.19	5.01	3.71	4.02	4.68	4.79
b	Young	6.66	6.95	4.12	6.87	7.53	6.10
c	Mature	5.30	6.86	5.99	7.80	7.80	6.41
d	Small scale	5.29	5.24	4.71	7.51	4.46	5.16
e	Medium scale	7.15	6.89	5.35	7.60	5.82	6.33
f	Large scale	4.76	7.47	7.55	7.27	7.98	7.31
g	All MFI sample	5.66	6.53	5.53	7.50	7.37	6.16
3	***Operating expense (% GLP)***						
a	New	28.16	39.71	42.03	37.78	51.25	40.13
b	Young	18.35	28.50	28.17	29.84	29.56	26.99
c	Mature	15.04	22.59	24.98	17.85	19.09	21.71
d	Small scale	19.00	37.93	32.73	21.00	55.23	30.99
e	Medium scale	14.85	27.94	23.77	19.81	42.86	24.11
f	Large scale	13.52	18.12	17.96	16.52	18.61	17.65
g	All MFI sample	16.61	26.99	26.43	19.52	24.53	24.48
	Provision for loan impairment (% GLP)						
a	New	1.93	1.69	1.84	0.54	4.29	1.96
b	Young	1.37	2.41	1.61	1.50	3.27	2.05
c	Mature	1.44	2.54	3.40	0.83	2.07	2.53
d	Small scale	1.35	1.92	1.87	0.90	2.54	1.72

e	Medium scale	1.54	2.73	2.53	0.84	2.58	2.27
f	Large scale	1.69	2.47	6.05	0.87	2.58	3.28
g	All MFI sample	1.47	2.34	3.00	0.87	2.58	2.37
4	***Net profit (% GLP)***						
a	New	-1.46	-2.12	-2.97	4.65	-6.72	-2.41
b	Young	2.48	4.42	4.16	7.13	1.72	3.87
c	Mature	2.00	3.94	0.02	5.20	5.04	2.19
d	Small scale	1.52	0.34	1.10	5.85	-0.67	1.29
e	Medium scale	1.98	4.11	3.12	5.27	0.83	3.36
f	Large scale	2.16	4.46	-4.27	4.31	3.76	1.76
g	All MFI sample	1.78	2.91	0.48	5.32	2.96	1.99
5	***Portfolio at risk after 30 days (% GLP)***						
a	New	3.67	3.92	1.76	13.76	5.76	3.83
b	Young	5.62	5.22	3.76	9.22	4.85	4.93
c	Mature	8.24	6.30	7.09	10.94	5.38	7.25
d	Small scale	7.46	5.28	6.68	12.33	8.29	6.87
e	Medium scale	7.05	6.15	6.48	11.00	6.14	6.88
f	Large scale	7.45	5.43	5.02	8.04	4.89	5.51
g	All MFI sample	7.34	5.57	6.23	10.91	5.32	6.42
6	***Average loan balance per borrower (per capita GNI)***						
a	New	1.09	1.17	0.32	0.44	2.42	1.06
b	Young	1.18	0.77	0.31	0.62	2.27	0.82
c	Mature	1.33	0.68	0.34	0.59	1.97	0.74
d	Small scale	1.33	0.87	0.23	0.58	0.61	0.65
e	Medium scale	1.14	0.80	0.35	0.54	1.63	0.68
f	Large scale	1.30	0.73	0.51	0.66	2.32	1.07
g	All MFI sample	1.27	0.80	0.33	0.58	2.08	0.79
7	***Female borrower (% total borrowers)***						
a	New	57.09	62.77	77.45	47.35	41.04	63.42

b	Young	54.14	61.20	79.77	53.62	41.42	64.41
c	Mature	56.82	59.52	75.16	50.65	57.63	65.65
d	Small scale	51.90	61.81	79.05	43.11	53.03	66.85
e	Medium scale	77.85	60.48	74.34	54.04	61.31	68.61
f	Large scale	39.90	59.59	71.94	61.50	50.69	59.84
g	All MFI sample	56.27	60.59	76.02	50.79	52.62	65.15
8	***Borrower per staff member***						
a	New	71.49	103.02	149.94	111.71	423.92	143.25
b	Young	104.89	127.56	155.25	107.40	116.51	130.89
c	Mature	118.08	138.32	158.30	107.60	113.91	139.03
d	Small scale	82.20	103.85	149.39	96.13	45.98	118.74
e	Medium scale	141.86	114.28	159.22	113.35	182.40	139.55
f	Large scale	142.79	160.66	171.34	120.23	162.10	160.37
g	All MFI sample	111.32	128.84	157.23	107.81	153.62	137.88
9	***Equity capital (% total assets)***						
a	New	24.93	44.68	49.27	25.58	41.82	42.28
b	Young	27.32	40.16	43.12	15.88	22.35	36.75
c	Mature	29.81	28.96	37.16	15.67	20.27	30.58
d	Small scale	31.81	48.12	44.65	19.66	36.15	41.00
e	Medium scale	30.13	35.37	36.53	13.97	37.92	32.99
f	Large scale	20.06	22.83	29.84	13.55	19.14	23.17
g	All MFI sample	28.86	35.05	38.98	16.26	23.30	33.16

Notes: (i) Definitions of variables are provided in Section 2 in the text. They are abstracted from MIX market database at: www.mixmarket.com. (ii) The categories New, Young and Mature MFIs have been in operation for 1 to 4 years, 5 to 8 years and more than 8 years respectively. (iii) The group of Small scale MFIs have gross loan portfolio (GLP) outstanding of less than US$2million in SSA, Asia, ECA and MENA. The figure for Latin America is less than $4 million. Medium-scale MFIs have GLP of between US$2million and US$8 million in SSA, Asia, ECA and MENA. The corresponding figure of Latin America is between US$4 million and US$15 million. Large scale MFIs in SSA, Asia, ECA and MENA have GLP of more than US$8 million while those in Latin America have GLP of more than US$15 million.

Appendix Table 2: Pairwise Correlation Analysis: Kendall's tau-b

Sample 2005 to 2010

Included observations after adjustment: 3980

	LYLD	***LFELR***	***LOPELR***	***LPFLR***	***LPRFTLR***	***LPAR30***	***LALPBP***	***LWBP***	***LBPSM***	***LECAR***
LYLD	1.000									
LFELR	0.159***	1.000								
LOPELR	0.478***	-0.042***	1.000							
LPFLR	0.148***	0.026***	0.167***	1.000						
LPRFTLR	0.176***	0.001	-0.052***	-0.124***	1.000					
LPAR30	-0.032***	-0.008	0.066***	0.247***	-0.188***	1.000				
LALPBP	-0.210***	-0.018*	-0.225***	-0.014	-0.013	0.085***	1.000			
LWBP	0.099***	0.002	0.121***	-0.022**	0.011	-0.132***	-0.389***	1.000		
LBPSM	-0.035***	-0.026***	-0.112***	-0.017	0.051***	-0.132***	-0.349***	0.285***	1.000	
LECAR	0.118***	-0.309***	0.153***	-0.002	0.153***	-0.028***	-0.059***	-0.013	-0.035***	1.000

Notes:(i) Asterisks *,**,*** indicate the statistical significance at the 10%, 5% and 1% confidence levels respectively. No asterisk means that the coefficient is not statistically different from zero. (ii) Definitions of variables and expected effects on interest income are provided in Section 2.2 in the text (iii) An L in front of a variable's name is for the natural logarithm. The measures of adjusted equity-to-asset ratio (LECAR) were expressed as the natural logarithm of one plus the respective variables in order to reduce the range of variation and surmount the problems associated with negative observations. According to MIX, the equity variable is adjusted for donations and other forms of subsidies(iv) Data is taken from the website of the MIX market at: www.mixmarket.com

Appendix Table 3: Regression results

Dependent variable: Natural log of portfolio yield (LYLD)

Methods: Panel two-stage least squares

	Column 1	Column 2
Explanatory variables	Model 1	Model 2
CONSTANT	0.179 [12.47]***	0.350[14.12]***
MATURE	0.005 [0.55]	-0.005 [-0.56]
MSCALE	0.052 [5.93]***	0.004 [0.41]
LSCALE	0.046 [3.78]***	0.017 [1.40]
MATURE*MSCALE	-0.041 [-3.94]***	0.0002 [-0.02]
MATURE*LSCALE	-0.051 [-3.98]***	-0.002 [-0.14]
MICROBANK	0.048 [0.60]	0.297 [4.22]***
MATURE*MSCALE*LSCALE*MICROBANK	-0.032 [-1.60]	0.010 [0.47]
LFELR	…..	0.016 [7.25]***
LOPELR	…..	0.074[14.09]***
LPFLR	…..	0.041 [1.04]
LPRFTLR	…..	0.143[11.46]***
LPAR30	…..	0.002 [1.31]
LWBP	…..	0.004 [0.99]
LBPSM	…..	0.010 [1.99]**
LECAR	…..	-0.008 [-0.52]
LALPBP	…..	0.224 [0.01]
LALPBPSQ		-0.114 [-0.01]
Cross-sections included	1112	952
Total panel (unbalanced) observations	6663	3980
Adjusted R-squared	0.512921	0.869733
F-statistic [probability]	7.25 [0.000]***	19.54[0.000]***
Durbin-Watson statistics	1.71	2.04

Notes: (i) Asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% confidence level respectively, (ii) Numbers in [….] are the estimated t-statistics, (iii) The dependent variable of all the models are the natural logarithm of nominal portfolio yield variable (LYLD), (vi) Definitions of variables are provided in Section 2.2 in the text. For brevity, estimates for cross-section and time-period dummies are not reported here, but are available from the author on request.