Are competitive microfinance institutions worth regulating? Evidence from Sub-Saharan Africa

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Abstract

There is increasing appetite for regulation of microfinance institutions after the 2008 financial crisis. Policy questions such as whether competitive microfinance institutions requires strong regulation to reduce, for example credit risk or competition and regulation operate in the opposite direction, which each tends to dampen the effect of the other, is an empirical issue that this paper provide answers based on data on Sub-Saharan Africa for the period 1995 to 2015, utilizing panel data approaches. Finding from the study indicates that low competition increases credit risk among MFIs, which regulation helps reduce such behaviour. The effect of regulation on credit risk is conditional on the level of competition, at the first percentile of competition; regulation does not reduce credit risk behavior of MFIs but does at competition level above the 25th percentile. Regulation on the other hand does not affect operational risk at any level of competition.

Key words: Financial services, regulation, microfinance, competition, portfolio risk

1. Introduction

Microfinance institutions play an important role in most developing countries as they provide

financial services, including poverty reduction intervention measures to a significant share of the population that is un-served by the formal financial institutions. About 2.5 million adult population of the World is unbanked in 2014 (World Bank, 2016), which majority live in Sub-Saharan Africa. The severity of the implication of such a huge size of the unbanked population on poverty alleviation and lack of job creations especially for SSA is that, majority, close to 90% of the unbanked population are in rural areas (Gentil and Servet, 2002), where poverty levels are endemic, with fewer job opportunities. Therefore, the lack of banking services to mobilize funds at lower cost for the impoverished rural population to create small business, invest into agriculture to provide the needed food requirement and earn some income, further perpetuate the incidence of poverty in such areas.

Over the recent decade, as a consequence of the problems associated with the poor not having access to the formal banking services on their livelihood, poverty outcomes and the associated social menace, couple with the promising positive effects that MFIs is making, especially in serving the poor unbanked segment of the population, has resulted in a plethora of different MFIs in developing countries, some with goals beyond the social intervention/developmental goals such as pure profit motives. This phenomenon is partly as a result of the success story of the microfinance model (Assefa et al. 2013), which leads to an increase in commercial oriented type of MFIs to enter the microfinance segment of the financial market.

The increase in MFIs from both types – development oriented MFIs and commercial oriented MFIs in recent years in developing countries, create competition among these firms to provide financial services to the poor. The increase in competition among MFIs due to the increase in the number of MFIs operating in the World financial market from 10 million in 1997 to more than 100 million in 2007

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(Assefa et al. 2013), creates some level of

competition

that may have negative consequences such as taking unnecessary risk in the quest to outcompete competitors for clients and markets.

Economic theory suggest that competition will result in lower prices for products produced due to lower cost of production, more output and generally a welfare improvement for the society relative to less competitive market environment. However, unhealthy competition may also result in competing firms taking unnecessary pricing, marketing, organizational and overall business strategies that exposes them to more risk. On the other hand, having few firms with significant power may also create excessive risk-taking behaviour in the absence of regulation as was the case in 2008 financial crisis. The question whether competition is good or bad will depend on the strength in these two opposing effects of competition relative to few firms with significant market power, the level of competition and whether the reference is to the firm, consumer/clients or society. If competition is creating more risk taking behavior relative to the lower prices and increase in output (outreach in the case of MFIs) effect, it is prudent that authorities regulate the microfinance market to curb competition and reduce the unnecessary risk-taking behaviour of the MFIs. Therefore, whether government should regulate MFIs will depend on whether competition was high and as a consequence, creating unhealthy competitive behavior among firms in the microfinance industry. If competition is not creating unhealthy outcomes and regulation is imposed, it will create a less favorable outcome than if regulation is not imposed.

The recent financial crisis has increased appetite for more regulation towards the financial sector in general and may also be the case for MFIs for countries that have experienced some ponzi scheme-types of operations of some MFIs such as in Ghana, DKM Diamond Microfinance Company Limited that went bust in mid 2015, due to its ponzi type of scheme it offered clients. But the policy maker will have to assess the two opposing effects to determine if regulation is necessary, especially in the case of MFIs given their core mandate to pool resources to provide micro loans to the segment of the society, who cannot access the main financial institutions such as banks for such micro loans. Therefore, whether it is optimal for government to regulate MFIs is conditional on the level of competition and the consequences thereof relative to less competition.

Whether the policy maker should regulate MFIs or not is an empirical question, which has not received much attention, especially in relation to risk taking behavior. To the best of our knowledge, there is no study in the MFIs literature that empirically examined the joint effect of regulation and competition on risk taking behavior of these firms, especially in the SSA context. The closest studies we have found in the literature are; Assefa et al. (2013), who looked at the effect of competition on performance; Hartarska and Nadolnyk (2011), Purkayastha et al. (2014) and Triki et al., 2017, they focused on the effect of regulation on performance or growth of the MFIs.

This paper aims to contribute to the literature through assessing the sequencing impact of risk (credit[1] and operational[2]), market concentration and regulation of MFI's in Sub-Saharan Africa. Contribution of this article is in three folds, first to provide an understanding of the nature of relationships between credit risk, competition and regulation of MFIs, second to assess whether regulation and competition reinforces each other or are substitutes in terms of their effect on credit risk and thirdly the role of both competition and regulation on operational risk of MFIs and whether their effects are different in comparison to their effect on credit risk. Literature

[1] Credit risk in this paper is measure as impaired loans to gross loans and advances.

[2] Operational risk on the other hand refers to lost due to poor management of loans and it is measured as the coefficient of variation of write-off ratio of loans by MFIs.

review and the general narrative on Sub-Saharan Africa shows that the factors examined by previous studies (Kablan, 2014; Cull et al., 2015; Ayele, 2015) focused merely on measurement effect of portfolio risk on profitability, outreach and repayment rates. The impact of regulation and market concentration jointly on credit (portfolio) risk of MFIs are omitted and therefore policy questions such as whether having a competitive MFI requires strong regulation to reduce for example portfolio risk (credit risk) or they operate in the opposite direction, which each tends to dampen the effect of the other cannot be comprehensively answered based on the exiting literature. This paper aims to provide some answers in that regard by providing an understanding of the relationships between risk (portfolio risk and operational risk) and both regulation and competition in the case of SSA, and in the process the policy implication thereof.

The central proposition of this empirical study is that MFIs portfolio risk is not independent of market competition and the regulatory environment. Efficient and optimum regulation assists to manage competition amongst MFIs that supports them to develop optimum

portfolios, operational procedures and reduce risk. The study builds lessons and the inferences of mainstream banks (Dewatripont, 2014; Berger et al., 2016) and lends support to the argument that portfolio adequacy, efficient and appropriate regulation and the market discipline affects the performance of MFI's. Therefore, there is a case to measure the joint effect of regulations and market competition on portfolio risk of MFI’s in Sub-Saharan Africa.

The empirical model

Based on the previous literature as discussed in the literature review section and coupled with the conceptual framework, the following reduced-form model is formulated for the empirical analysis to answer the research questions raised in the introduction section of the paper. The extant literature on determinants of a portfolio (credit) risk suggests that it is influenced by firm-specific factors such as the size of the business, the financial cost of the MFI, operational efficiency of the MFI, financial strength and financial revenue of the MFI. Also, both theory and policy discussions suggest that both competition and regulation are key market and policy variables that influence the risk-taking behaviour of firms in general including MFIs. Based on this, the reduced-form model is specified as;

$$\ln Risk_{it} = \beta_0 + \beta_1 Regulation_{it} + \beta_2 \ln Competion_{it} + \beta_3 Regulation_{it} * \ln Compe \quad (1)$$

Where risk in this study will focus on two different aspects of risk, credit risk and operational risk, regulation is measured as a dummy variable that takes a value of 1 if the MFI is regulated and 0 for unregulated MFI, competition is measured using two different competition index (Lerner index, Herfindahl-Hirschman index), $\boldsymbol{X}$ is a vector of controls that include business size proxy with gross loan portfolio, financial cost of the microfinance firm proxy with cost per loan, operational efficiency of each microfinance firm proxy with write off ratio, financial strength of microfinance firms proxy with yield on gross portfolio, financial revenue proxy with interest and fee income and both firm (η_i) and time fixed effects (μ_i) to account for unobserved heterogeneity, ε_{it} is a random error term. From equation (1), the total impact of regulation on risk is given by taking the partial derivative of risk with respect to regulation, which is express as:

$$\frac{\partial \ln Risk_{it}}{\partial Regulation_{it}} = \beta_1 + \beta_3 \times \ln Competition_{it}$$

On the other hand, the total effect of competition on risk is given by taking the partial derivative of risk with respect to competition based on (1), which is specified as:

$$\frac{\partial \ln Risk_{it}}{\partial \ln Competion_{it}} = \beta_2 + \beta_3 \times Regulation_{it}.$$

We adopt a fixed effect approach that controlled for potential endogeneity problem associated with risk and regulation. The potential endogeneity problem due to possible reverse causation between risk and regulation is resolved by estimating a second-reduced form equation for regulation as specified in equation (2), where the residuals for this equation is generated and added into equation (1) as an additional covariate (two-stage residual inclusion approach). The purpose is to control for the endogeneity problem caused by the reverse causation between risk and regulation. This approach has been suggested and used by prior studies such as Hausman (1978), Das et al. (2003), Blundell and Powel (2004), Terza et al. (2008) to deal with issues of endogeneity when there are no suitable available instruments. We assumed that risk, competition and firm characteristics are vital factors that influence the level of regulation of MFIs and therefore specify the reduced-form model as:

$$Reglation_{it} = \alpha_0 + \alpha_1 \ln Risk_{it} + \alpha_2 \ln Competion_{it} + \theta' \mathbf{X}_i \qquad (2)$$

where all the variables are the same as defined for equation (1), e_{it} is a random error term.

Estimation methodology

Our estimation strategy follows three steps. In the first step, we estimate equation (2) using fully parametric econometric methods (panel probit model since regulation is a dummy variable) appropriate for panel analysis to generate the residuals for the main equation (1) of interest to control potential endogeneity problem. We then estimate equation (1) to assess our fundamental questions.

The models presented in both equation (1) and (2) are estimated using fixed effect estimation approach. The estimation strategy is in two steps. In the first step, we estimate regulation model and save the residuals to be included in the risk model. The purpose of this is to reduce potential endogeneity problems due to the interdependence between risk and regulation. In the second step, we estimate the risk model, both for credit risk and operational risk. In the final stage, we perform sensitivity analysis on our main results by relaxing the static structure imposed in estimating equations (1) and (2) to a dynamic structure. In the case of the dynamic model, the usual fixed effect model will not be appropriate because of the included lag dependent variable as a regressor will be correlated with the fixed effect, creating a dynamic panel bias (Nickel bias), which is severe in small panels. Since our panel time dimension is less than 30 years, the threshold level where Nickel bias is not critical (Judson and Owen, 1999), we need to apply the appropriate methods to reduce the effects of Nickel bias.

In the literature both the corrected least squares dummy variable (LSDVC) and the GMM estimators were deigned purposely to handle dynamic panels to correct for Nickel bias, especially in panels with short time periods, where the bias is severe. In panels with period above 30 years, the bias created by the correlation between the lagged dependent variable and fixed effects is small (Judson and Owen, 1999). In such instances, the FE estimator performs well relative to both the GMM and LSDVC. In this study, we opted for the LSDVC to correct for the bias created by the lagged depended variable in the dynamic model estimation.

4. Data and Results

Data

The data for the study is from the MIX Market dataset that covers the period 1995 to 2015 for 3856 microfinance firms for SSA countries. The dataset is a panel, but due to differences in the year of operations across different MFIs within and between countries in the dataset, we have an unbalanced panel. Also due to missing observations for some of the variables, our final sampled reduced to 1574 firms. The variables in the dataset that is important for the study are provided and described below.

MFI credit risk is measured as impaired loans to gross loans and advances and used as the dependent variable in this study. Chaibi and Ftiti (2015) argue that credit risk measured as impaired loans divided by gross loans is a better representation of credit risk as it reflects actual credit risk or loss that pertains to a specific time The portfolio at risk is used as a proxy and is estimated as the proportion of the loan portfolio of an MFI that is overdue for 30 days and is at risk of not being settled. Differently phrased, the portfolio at risk >30 variable reflects the actual risk of a delinquency problem because it takes into account the full amount of the loan at risk predominantly when the loan payments are small (Ledgerwood, 2000). Portfolio in itself specifies the aggregate incomes accessible for the MFI to disburse it as credits to its customers. Portfolio quality is a way of determining how best the organization can safeguard its portfolio. It is a crucial aspect of performance evaluation, as it is the most significant source of risk for most business organisations that exists in their assets portfolio. Hence, to their best effort, MFIs need to sustain the value of their investments. For our study, we consider portfolio at risk over 30 days (PAR >30 days) as used in Assefa et al. (2013). We include this variable to determine how well an MFI is managing its risks as it provides services to its clients.

Operational risk is defined as lost to the MFI due to poor management of loans. This is proxied by computing the coefficient of variation (CV) of write-off ratio of loans by MFIs. The CV is then used as a proxy for operational risk.

The dataset also contains information on whether the MFI is regulated or not. Regulation is measured as a dummy variable that takes a value of 1 if the MFI is regulated and 0 if it is not regulated. This is to determine whether regulated MFIs are exposed to more risk than their counterparts. Gietzen (2017) found no association between regulation (regulatory quality from the World Bank governance indicators) and risk exposure and thus conclude that regulators might see no need intervening in the sector due to seemingly lower liquidity risk. Their regulatory index is generic at the country level, not MFIs specific regulation and therefore considering MFIs related regulation will likely provide a better understanding of the role of regulation on risk-taking by MFI. To the best of our knowledge, the only available MFI regulatory variable is the dummy variable in the MIX Market dataset that indicates whether the MFI is regulated or not. We, therefore, rely on this variable as our regulation variable.

Competition is one of the critical variables for our study. However this variable is not readily available, we preferably have to compute it by considering existing literature on the best measure for competition. There is no unanimity in the literature of the optimal way to measure competition. The Lerner index is our primary choice to proxy competition due to its relatively good properties as presented in the next paragraph. The inclusion of competition for the analysis is to assess whether risk-taking behaviour of MFIs increases with competition or otherwise. It is crucial to include competition because the risk faced by MFIs might be influenced dramatically due to the competitive nature of the market in which they operate.

The Lerner index is our measure of MFI-level of competition. The index ranges between 0 and 1, where a value close to zero is an indication of strong competition, while close to 1 suggest less competition. The index is of the form LI $=\frac{P \ \ -MC}{P}$, where p is the output price proxy by yield on gross loan portfolio and MC, is the marginal cost of the firms. High (low) index imply low (high) competition. In estimating the Lerner index, we follow an approach by Assefa et al. (2013), by constructing a translog cost function as follows;

$$\ln TC_{it} = \beta_0 + \beta_1 \ln y_{it} + \tfrac{1}{2}\beta_2 \ln^2_{it} + \sum_{k=1}^{2}\gamma_k \ln w_{kjt} + \tfrac{1}{2}\sum_{i=1}^{2}\phi_k \ln y_{it} \cdot \ln w_{kjt} + \sum_{k=1}^{2}\sum_{j=1}^{2}\theta \ln w_k$$
$$+ \rho trend + \tfrac{1}{2}\tau tend^2 + \sum_{i=1}^{2}\zeta_i \ln w_{j\,jt} \cdot trend + \delta \ln y_{it} \cdot trend + \varepsilon_{it}$$

(3)

and take the first derivatives with respect output to obtain the marginal cost function as shown below

$$MC_{it} = \frac{TC_{it}}{y_{it}}\left[\beta_1 + \beta_2 \ln y_{it} + \sum_{k=1}^{2}\phi_k \ln w_{k,it} + \delta trend_{it}\right].$$

(4)

We then estimate the marginal cost function because it cannot be inferred directly from the data. The advantages of the Lerner index relative to other measures of competition are: (i) Lerner index enables us to investigate competition at the firm-level; (ii) It varies over time which again gives us the opportunity to measure competition over some years (Assefa et al., 2013).

In estimating the marginal cost in equation 4 above, the following variables were used. First the total cost for each firm, which is the aggregate of all expenses incurred by an MFI in a given financial year. It consists of both operating and financial expenses that the firm incurred in running the affairs of the business. The sum of operating and financial expenses incurred by the firm is used to proxy for this.

The output variable (y) for each MFI is the gross Loan Portfolio, which consists of all outstanding principal for all outstanding client loans, including current, delinquent and restructured loans, but not loans that have been written off. It does not include interest receivable and employee loans. In constructing the cost function, we considered only two inputs, which are very crucial to the operations of microfinance institutions. These include cost of labour and capital. The cost of capital refers to the cost of equity and debt used in financing the microfinance business. It is the opportunity cost of taking a specific investment. It is measured as the ratio of financial expenditure to total liabilities of the firm within the financial accounting year.

The cost of labour, on the other hand, consists of both direct and indirect cost incurred by employees for rendering services to the firm. In estimating the labour cost, the study took the ratio of personnel expenses to total assets as a proxy, with the assumption that the primary component of operating costs is the personnel salaries. To control for important unobservable such as technology, we included a time trend to take care of technological change or capture movement of the cost function over time and MFI-specific fixed effects. This is to cater for related variances in the cost structures among MFIs and unobserved MFI heterogeneity.

Key control variables in our credit and operational risk model include business size, measured as the natural log of gross loan portfolio. Following the economies of scale and diseconomies of scale theories, the study expects a positive or negative effect of MFIs size on credit risk. That is following economies of scale; larger MFIs have the needed resources, both financial and human and the capacity to monitor and supervise their customers or borrowers; thus reduction in credit risk. However, following diseconomies of scale larger MFIs are overwhelmed by their size causing replication of functions and idle resources to monitor clients, which could result in increased credit risk. For instance, Williamson (1967) and Himmelberg et al. (1999) prove that as the size of a financial institution become too large, it results in inefficiencies in monitoring and evaluation of clients due to the massive cost of operation; therefore, leading to increased credit risk.

In addition to the size of the firm, we also control for financial cost of MFI. This is the cost the firm incurs in disbursing loans to their clients. Once, loans are the primary product for microfinance activity; we proxy financial cost with the cost per loan. It is measured as the ratio of financial expenses to gross loan portfolio to determine per unit cost of distributing loans to customers. The essence of this is to indicate the efficiency of MFIs in its loans disbursement.

Operational Efficiency of MFIs is also controlled for in our estimations. This is a performance measure that shows how well MFIs is rationalising its operations and takes into consideration the cost of the input and the price of output. Efficiency in expense management should ensure a more efficient use of MFIs loanable resources. It is proxy with write off ratio. It is the ratio of total amount of loans written off to gross loan portfolio (Kinde, 2012). High (low) ratio indicates low (high) efficiency of management.

The last controlled variables in model are financial strength and financial revenue. Financial strength measures the soundness or profitability of a company. It measures the firm's ability to generate positive net incomes for a given level of investment. This variable also determines how well management is running the affairs of the business in the interest of shareholders. We proxy financial strength with yield on gross loans portfolio obtain from the MIX market database. The yield is the net incomes from gross loans of an MFI. Financial revenue, on the other hand, is some incomes that a firm generates through its activities within a specific period. Includes revenue generated from both the gross loan portfolio and investments. It measures the total amount of money that accrues to an MFI in a given financial year. It determines how well management will be able to meet their financial obligation. The variable is proxy with interest and fee income on transactions. The descriptive statistics for the entire key variables described above is presented in the appendix (Table A3).

Results

3.2 Results of the empirical estimation

We first present the results based on a fixed effect model both for credit risk and operational risk in that sequence and provide some discussion on the results and later present sensitivity analysis by relaxing the static model imposed to obtained our main findings and also using a different index to measure competition and the implication of the sensitivity analysis on our primary results.

Credit risk results

In Table 1, we present the credit risk results based on a fixed effect model. Table 1 contains three columns, each represent a unique version of the fixed effect model, first column (1) is a model without both the interaction between regulation and competition, and time dummies, the second column (2) is based on a model without time dummies, and the third column (3) is based on our specified model presented in equation (1).

In all cases, we find a significant positive direct effect of regulation on credit risk across the three different specifications, with an increasing magnitude as one moves from column (1) to column (3). This is just the direct effect of regulation since the estimated coefficient of the interaction term in column (3) is negative but significant at any of the conventional levels of significance, it, therefore, implies that the estimated regulation coefficient presented in columns (1) and (2) are tentatively the direct effects of regulation, but the indirect impact via its interaction with competition is not captured by the models estimated and presented in columns (1) and (2), respectively. The negative coefficient of the interaction term between regulation and competition implies that the total effect of regulation on credit risk could be positive or negative depending on the level of competition via taking the partial derivative of credit risk with respect to regulation, which is presented in the model section after equation (1).

The estimated total effect of regulation evaluated at different percentiles, 1st, 25th, 50th, 75th and 95th respectively are all significant at the 5% significance level except at the 25th percentile, where it is not significant. This result is reported in table 4 and revealed that the total effect of regulation on credit risk is conditional on the level of competition. The impact is positive at 1st percentile level of competition (high competition) and turns negative (significant) on the 50th, 75th and 95th percentiles (low level of competition) of competition proxy by Lerner index. The table further revealed that the magnitude of the negative interaction effect increases as percentile level increases, suggesting among other things that a very low competitive microfinance industry should be regulated if the policy target is to reduce credit risk exposure. However, if the level of competition is high as demonstrated by 1% percentile level of competition, regulation is bad for credit risk. This is because regulation of a competitive MFIs may induce some market power for the existing firms, which could result in more risk-taking behaviour for pure profit motives. Also, in a high competitive market, with very many firms, effective regulation may be difficult to achieve and in such an environment, an ineffective regulation may rather induce reckless credit risk-taking behaviour by competing MFIs, where the MFIs in the industry will not adhere to rules and regulation provided by the policymaker or regulator to ensure a smooth and less risk-taking activities among MFIs.

Table 2: Regression results from estimating a fixed effect static model for portfolio risk

Variables	(1) Credit risk (log)	(2) Credit risk (log)	(3) Credit risk (log)
Regulation	0.742***	1.354***	1.395***
	(0.245)	(0.347)	(0.337)
Competition (log Lerner Index)	0.125	0.251	1.802***
	(0.214)	(0.206)	(0.433)
Regulation* competition (log Lerner Index)			-1.589***
			(0.393)
Size (log)	0.157***	-0.079	-0.088
	(0.056)	(0.076)	(0.075)
Financial Cost (log)	-0.031	-0.033	-0.033
	(0.027)	(0.027)	(0.026)
Operational Efficiency	0.041	0.027	0.029
	(0.144)	(0.141)	(0.145)
Financial Revenue (log)	-0.065***	-0.054**	-0.049**
	(0.025)	(0.024)	(0.024)
Financial strength (log)	-0.100**	-0.097*	-0.086*
	(0.051)	(0.051)	(0.050)
Residual (regulation residual)	-0.296***	-0.533***	-0.742***
	(0.107)	(0.147)	(0.156)
Constant	-5.154***	-2.766***	-2.659***
	(0.881)	(0.997)	(0.989)
Time dummies	no	yes	yes
Observations	1,574	1,574	1,574
Number of firms	444	444	444
CVS	1.155	1.122	1.105

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, cvs denotes cross validation score. Note competition have inverse interpretation as higher values implies lower competition, while lower values denotes high competition.

Table 3: Total effect of regulation evaluated at different percentiles of competition.

Percentile of competition (Lerner index)	1%	25%	50%	75%	95%
Total regulation effect (FE model)	1.330***	-0.344	-1.811**	-2.760**	-2.792**
	(0.30)	(0.54)	(0.89)	(1.12)	(1.13)

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The estimated direct effect of competition is positive and significant at any of the conventional significance levels. The estimated direct elasticity between credit risk and competition is about 1.8, which is also the total effect of competition on credit risk for non-regulated MFI since the interaction effect evaluated for non-regulated MFI is zero. On the other hand, the total impact of competition for regulated MFI is 0.213, which is calculated by adding the coefficient of the interaction term (-1.589) to the coefficient of competition (1.802) via the partial derivative of credit risk with respect to competition as expressed in the model section. This implies that non-regulated MFIs tend to take more risk if they operate in less competitive environment relative to regulated MFIs. The transmission mechanism is as follows, without regulation, MFIs enter the industry for all manner of reasons including serving the poor and for commercial purposes, as a consequence these MFIs tend to take more risk for profit motives due to the laxed rules governing their operations. Few big MFIs can utilise unfair competitive strategies to dominate the market to gain some market power. Given the power, they will be taking excessive risk in the absence of regulation. This means that, given a less competitive environment, regulation will tend to reduce credit risk exposure.

Among the control variables, only the estimated coefficients on financial revenue, financial strength and the residuals from estimating a regulation model (included to control potential endogeneity of regulation in our credit risk model), are statistically significant. The estimated elasticity between credit risk and financial revenue is -0.05, while that between credit risk and financial strength is -0.09. These results imply that MFIs tend to take less credit risk when their financial revenue position is high. MFIs with excellent financial strength also tend to make less credit risk, which is very intuitive. This is because MFI with good financial revenue position and excellent financial power will not take unnecessary credit risk exposures. Besides, MFIs with such good and excellent financial revenues and financial strength are more likely to make strict screening measures to reduce risk exposures relative to those without such financial standing, as they are not under severe revenue and liquidity pressure to venture into taking unnecessary credit risk.

Operational risk results

Next, we assess whether regulation and competition matter regarding operational risk of MFIs in SSA. Thus, giving the finding that both competition and regulations are essential factors to consider when implementing policies to reduce credit risk among MFIs, does this also apply to operational risk? In addressing this objective, we similarly estimated an operational risk model as done in the case of credit risk. We assessed three different versions, which are reported under three different columns in table 4. Column (3) is estimated based on the model presented in eqn (1), while column (2) excluded the interaction between regulation and competition and column (1) excluded both the interaction term and time dummies. The reported results indicate that regulation is not essential for operational risk of the MFIs since the estimated coefficient is statistically insignificant across the three different versions at any of the conventional significance levels. A possible explanation for this is may be that most of the regulation of MFIs is directed towards loans activities but less towards how the MFIs operate. As a consequence, in such a case, regulation is likely to be associated with loan and credit activities of these institutions, but less to operational activities.

Competition, on the other hand, increases operational risk of MFIs, since the estimated coefficient is positive and significant at least at the 5 percent significance level, meaning that a less competitive MFIs industry is associated with high operational risk. The interaction term between regulation and competition is however insignificant, further supporting the finding from the direct effect of regulation on operational risk. In a nutshell, regulation does not affect operational risk of MFIs in our sample, both direct and indirect.

The estimated coefficient of size is negative and significant, implying that the size of the MFI has an impact on operational failures and hence operational risk. The mechanism for this is as follows; large firms can afford better systems and implement relatively better policies and procedures on the average relative to small firms. The implication of this is that large firms on the average can reduce employee errors due to better screening process and monitoring procedures, reduce system failures and in general reduce events that are likely to create problems for the firm's operations.

Table 4: Regression results from estimating a fixed effect static model for Operational risk

Variables	(1) Operational Risk (log)	(2) Operational Risk (log)	(3) Operational Risk (log)
Regulation	-0.012	0.010	0.021
	(0.066)	(0.095)	(0.094)
Competition (log Lerner Index)	0.215***	0.205***	0.283**
	(0.060)	(0.063)	(0.111)
Regulation*competition			-0.081
			(0.095)
Size (log)	-0.102***	-0.092***	-0.092***
	(0.013)	(0.017)	(0.017)
Financial Cost (log)	0.005	0.003	0.003
	(0.008)	(0.008)	(0.008)
Operational Efficiency	-0.057*	-0.064*	-0.062*
	(0.033)	(0.033)	(0.033)
Financial Revenue (log)	0.008	0.007	0.007
	(0.008)	(0.008)	(0.008)
Financial strength (log)	0.016	0.013	0.013
	(0.012)	(0.012)	(0.012)
Residual (regulation residual)	0.017	0.011	-0.005
	(0.027)	(0.039)	(0.041)
Constant	-0.076	0.076	0.081
	(0.215)	(0.258)	(0.258)
Time Dummies	no	yes	yes
Observations	2,144	2,144	2,144
R-squared	560	560	560
CVS	0.147	0.147	0.147

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, cvs denotes cross validation score

The results also revealed that operational efficiency has a significant negative effect on operational risk of MFIs, which among other things means that if the firm is operating efficiently, the firm tends to be less prone to failures in procedure, systems and policies and as a consequence reduce employee errors, system failures, reduction in criminal activities and any action that will disrupt the firm's business process. This ultimately reduces the cost associated with operational failures and hence operational risk.

The other controls such as financial revenue, financial strength and financial cost are not statistically significant at any of the conventional significance level, which implies these controls have no impact on MFI's operational risk exposures, contrary to the findings from credit risk.

Sensitivity analysis

Our primary results reported in table 2 and 4, may be sensitive to the type of structure imposed on the model (a static model for the primary results). To assess the implication of the imposed structure of the model on the results, we relax the static nature of the model by estimating a dynamic model. The results based on a dynamic model are reported in table A1 in the appendix. The results revealed, in general, they are qualitatively similar to our primary results for both the credit risk results and the operational risk results. They were only slightly different regarding size of the coefficients. Our general conclusion based on this sensitivity analysis is that the results are robust to the model structure (static or dynamic) for both the credit risk and operational risk models.

The general conclusion from the sensitivity analysis is that in general, the type of model structure imposed (static versus dynamic) does not significantly influence the model results. In the case of the choice of proxy for competition, we found estimates on the key variables of interest (regulation and competition) are sensitive to the proxy used for competition (HHI versus Lerner index).

4. Summary and Conclusion

The study highlights the sequencing impact of portfolio risk, market concentration and regulation of MFI's in Sub-Saharan Africa. To establish this, we use both fixed effect and dynamic panel regression models on a sample of 3856 microfinance firms from Sub-Saharan Africa countries for the period 1995 to 2015. Evidence from our extensive panel fixed effect, and dynamic models suggest a significantly positive direct impact of regulation on credit risk. The result implies that regulation substantially affects credit risk positively.

In a similar evidence, the findings also suggest a significantly negative relationship between the interactive term of regulation and competition. This indicates that a low competitive MFI industry could be efficiently regulated if the policy target is to reduce credit risk exposure. This is because; regulation will control reckless credit risk-taking behaviour by powerful MFIs to ensure that MFI in the industry adheres to rules and regulation provided by the policymaker or regulator to aid a smooth and less risk-taking activities among MFIs.

Contrary to the above evidence, we did not find any significant relations between regulation and operational risk. A possible explanation for this is that most of the regulation of MFIs is directed towards loans activities but less towards how the MFIs operate. Consequently, regulation is likely to associate with loan and credit activities of these institutions, but less to operational activities. However, we find the estimated coefficient of competition on operational risk to be positive and significant, which suggests that low competitive MFI's are very much exposed to high operational risk.

Our general conclusion based on this sensitivity analysis is that the results are robust to the model structure (static or dynamic) for both the credit risk and operational risk models. The results remain consistent after controlling for model structure (static or dynamic).

Our results offer empirical evidence for academic literature on microfinance and policymakers. First, the study provides for the first time empirical evidence on the relationship between regulation, competion and risk-taking behaviour of MFI's unlike, most previous studies (Kablan, 2014; Cull et al., 2015; Ayele, 2015), that investigates whether regulation and competition have different effects on credit risk and operational risk. Our model reveals that regulation is likely to associate with loan and credit activities of these institutions, but less to operational activities. Against this backdrop, we suggest further studies to control for these conditions to derive reliable conclusions.

Second, our findings suggest that MFI industry could be regulated efficiently if policymakers develop policies targeted at reducing credit risk exposures of MFI's than their exposure to operational risk. Third, the findings also offer a guide to business owners on the type of risk exposure they may be exposed to under different market conditions. Our model reveals that low competitive MFI's are very much likely to be exposed to high operational risk. The main limitation of this study is that the above findings are restricted to Sub-Saharan African countries. Further and more extensive analyses in multiple contexts and countries will help to establish causal effects between the variables.

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Appendix

Table A1: Regression results from estimating a Least Squares Corrected Dummy Variable dynamic model for operational risk and portfolio risk

Variables	(1) Operational Risk (log)	(3) Credit risk (log)
Lag Credit risk (log)		0.460***
		(0.033)
Lag Operational risk (log)	0.080***	
	(0.016)	
Regulation	-0.009	0.853*
	(0.121)	(0.493)
Competition (Lerner index (log))	0.254**	1.879***
	(0.112)	(0.491)
Size (log)	-0.096***	-0.087
	(0.020)	(0.107)
Regulation*competition	-0.051	-1.491***
	(0.174)	(0.539)
Financial Cost (log)	0.004	-0.022
	(0.007)	(0.052)
Operational Efficiency	-0.059*	-0.130
	(0.034)	(0.254)
Financial Revenue (log)	0.006	-0.044*
	(0.004)	(0.024)
Financial strength (log)	0.011	-0.053**
	(0.007)	(0.022)
Residual (regulation residual)	0.009	-0.509**
	(0.037)	(0.224)
Time dummies	yes	yes
Observations	2,017	1,174
Number of firms	521	324

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A2: Descriptive statistics for the dataset for the analysis for overall, where data is pooled cross firms and time period, within firms and between firms.

Variable		Mean	Std. Dev.	Minimum	Maximum	Observation
Portfolio risk	Overall	.1003945	.1999645	0	6.8431	N = 240
	Between		.196727	0	2.4395	n = 62
	Within		.1402733	-2.263706	4.503995	
Regulated	Overall	.7733402	.4187249	0	1	N = 385
	Between		.3242735	0	1	n = 81
	Within		.3274483	-.1641598	1.606674	
Gross loan Portfolio	Overall	1.63e+07	1.07e+08	0	3.40e+09	N = 369
	Between		5.31e+07	0	1.01e+09	n = 80
	Within		7.80e+07	-9.52e+08	2.41e+09	
Cost per loan	Overall	261.8104	482.4167	4	6822	N = 117
	Between		453.8537	5	4164	n = 52
	Within		305.9791	-2542.69	4367.477	
Write of Ratio	Overall	.0483115	.6478182	-.0226	25.7114	N = 189
	Between		.2129455	0	3.722914	n = 52
	Within		.598914	-3.674603	22.0368	
Financial Strength	Overall	2074.507	91062.65	-1.9587	4100000	N = 202
	Between		40741.08	-.799	1025000	n = 63

	Within		78886.22	-1022926	3077074	
Financial Revenue	Overall	52137.63	407119.2	-2057.86	1.50e+07	N = 385
	Between		274067.7	0	5000507	n = 81
	Within		339063.1	-4948369	1.01e+07	
Lerner Index	Overall	.7021866	.1563465	.0408438	.9736672	N = 235
	Between		.1476259	.0906654	.9736672	n = 59
	Within		.0837732	.1386373	1.02605	
HHI	Overall	.0020666	.0087519	0	.1153031	N = 385
	Between		.0068352	1.38e-09	.1153031	n = 81
	Within		.0073305	-.0442163	.107293	
Total cost	Overall	5581175	3.08e+07	4.8849	8.20e+08	N = 238
	Between		1.84e+07	97.21364	3.85e+08	n = 60
	Within		1.85e+07	-2.81e+08	4.41e+08	
Labour Cost	Overall	12937.26	11423.95	.850725	244348.8	N = 215
	Between		10401.21	1.136196	90979.57	n = 54
	Within		6782.434	-22465.18	221594	
Capital Cost	Overall	.0634976	.2066092	.0000155	6.644397	N = 219
	Between		.3190487	.0005133	6.644397	n = 56
	Within		.0876861	-1.653894	2.138548	
Market share	Overall	.0098437	.0324453	0	.627721	N = 369
	Between		.0223006	2.40e-08	.2397155	n = 80
	Within		.0275026	-.1512378	.54601	