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Credit risk in microfinance industry: Evidence from sub-Saharan Africa

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Abstract

Paradoxically, a plethora of empirical evidence in the traditional banking industry claims that smaller loans are associated with higher risk and the exact opposite is true for large loans. In this study we investigate these claims by estimating the relationship between loan sizes and credit risk in the microfinance industry. The sample used for our analysis incorporates over 2000 annual observations, and 632 microfinance institutions drawn from 37 countries of the sub-Saharan African (SSA) region over the period 1995 to 2013. Using the GMM technique, our estimates indicate that credit risk is positively related to loan sizes among microfinance institutions operating in SSA. Our findings have significant implications for the portfolio managers of microfinance institutions operating in SSA, particularly in light of the current wave of mobile money services in many countries.

JEL classification: C33; G21; G32; O12; O55

Keywords: Credit risk; Female borrowers; Loan sizes; Microfinance; sub-Saharan Africa

1. Introduction

In the last two decades, the microfinance industry in sub-Saharan Africa (SSA) has been growing rapidly at a rate of over 10% per annum (Chikalipah, 2017a). The unprecedented growth of the microfinance industry stems from a disappointing situation; the persistent failures of many traditional banks, if not all, to extend their financial services to the poor in society (Allen et al., 2011). Markedly, not only is microfinance the industry that is increasingly becoming the core of financial inclusion, but also it is an important instrument of consumption smoothing among the poor in the SSA region (Morduch, 2000). For example, between 2010 and 2015, the agriculture micro-insurance market grew in access of 400% (Kuwekita et al., 2015).[1] In addition, mobile money services are the fastest growing segment of microfinance, with over 100 million active mobile money users in the SSA (Jack and Suri, 2014).[2] In some countries, including, Burundi, Cameroon, Chad, Democratic Republic of Congo, Gabon, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Rwanda, Swaziland, Tanzania, Uganda, Zambia, and Zimbabwe, there are more mobile money accounts than bank accounts (Asongu, 2015).

Against this background, providing microcredit to the poor entails overcoming credit risks. The credit risks in the microfinance industry are often amplified, mostly, by two main factors: (i) lack of a collateral pledge by borrowers; and (ii) the information asymmetry between borrowers and lenders. Theoretically, these two problems are alleviated by regular monitoring, and group lending (Emekter et al., 2015). Besides that, empirical evidence in the microfinance industry indicates that targeting female borrowers significantly reduces credit risk (Agier and Szafarz, 2013; D'Espallier et al., 2011, 2013; Strøm et al., 2014).

A mounting body of empirical studies in the microfinance industry found that credit risk is negatively affected by a group

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[1] Micro-insurance is one of the products offered by microfinance institutions; other main products and services include: microcredits, microsavings, micro-housing units, micro-consignments, micro-franchises, micro-enterprise trainings, and mobile money services.

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[2] Further, mobile money services differ slightly from mobile banking services. The mobile money services allow, predominantly, poor people to access financial services using mobile phones without having a formal bank account. By contrast, mobile banking services allow people to use mobile phones to manage their bank accounts.

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lending methodology, targeting women borrowers and the level of lending interest rates (Ayayi, 2012; Crabb and Keller, 2006; Krauss and Walter, 2009; Lassoued, 2017; Nkamnebe and Idemobi, 2011). Yet, we are unaware of any study in the microfinance industry that has explicitly investigated the relationship between credit risks and loan sizes.[3] It is this gap in the research that this study attempts to fill, and it will provide the empirical findings on the connection between credit risk and loan sizes, in the perspective of the microfinance industry. It is worth noting that the relationship between credit risk and loan sizes has been extensively analysed in the traditional banking industry (for examples, check: Ali and Daly, 2010; Berger and Udell, 1990, 1995; Booth, 1992; Harhoff and Körting, 1998; Jiménez and Saurina, 2004; Leeth and Scott, 1989).

There are several incentives for undertaking an empirical investigation on the nexus between credit risk and loan sizes in the microfinance industry of SSA. Firstly, this is partly due to commercialisation and mission drifts, in which many microfinance institutions are converting from being non-profit to profit orientated. The microfinance institutions (MFIs) that are profit oriented habitually target salaried workers and micro-businesses with relatively large loan amounts. Furthermore, profit oriented MFIs rarely exploit the group lending methodology (Agier and Szafarz, 2013; D'Espallier et al., 2011; Kevane and Wydick, 2001; Mersland and Strøm, 2010). Relatedly, the advent of mobile money services, that enables users to access microfinance products via the use of a mobile phone, has immensely reduced the joint liability lending in the microfinance industry in SSA. In the microfinance industry group lending permits the poor to replace physical collateral with social collateral. Secondly, this study will verify the extent to which the theoretical credit risk approaches, which are applicable in traditional banking, hold fast in the microfinance industry. Doing so will improve an understanding of credit risk modelling in the microfinance industry. Thirdly, and lastly, the gap in the research is one of the motivations for this paper, and aims to fill that void and provide empirical evidence on the effect of loan sizes on the credit risk of MFIs operating in the SSA region.

In light of that, we study the seemingly paradoxical relationship between loan sizes and credit risk in the microfinance industry of SSA. To do so, we utilise the microfinance firm level dataset, exclusively obtained from the Microfinance Information eXchange (MIX), which contains over 1300 annual observations. Moreover, the final sample comprises of 632 microfinance institutions, domiciled in 37 sub-Saharan African countries, and the data covers the period from 1995 to 2013. Our analysis approach is decidedly empirical, and we use the generalised method of moments (GMM) and fixed effects (FE) estimators. We apply different estimation techniques to verify the robustness of our baseline results. The robustness checks include: (i) the re-estimation of our model specification without the control variable, which is the lending interest rates variable; (ii) we also re-run our estimation model with Winsorized variables, and this approach has modified the spurious outliers in our sample (Dixon, 1960); and (iii) we test the validity of the instrument set of GMM estimates. Briefly, and without overshadowing the main empirical findings of this study, our estimates indicate that credit risk is positively and significantly related to loan sizes in the microfinance industry of the SSA region.

The rest of the paper proceeds as follows. The next section reviews the empirical studies with particular attention devoted to the studies that investigated the credit risk in the microfinance industry. Furthermore, we also undertake a brief review of the literature that investigated the relationship between credit risk and loan sizes in the traditional banking industry. Section 3 presents the motivating theoretical model, and our estimation framework. In Section 4, we describe the data used in this study. Thereafter, in Section 5, empirical results are presented and discussed. Section 5 presents the baseline results, and Section 6 provides further results and robustness checks. Section 7 offers the summary and concluding thoughts for this study. Appendix A provides further information about the distribution of the MFIs into respective countries sampled in this study. Appendix B outlines the derivation of Cook's Distance methodology.

2. Literature review on the credit risk in microfinance

As earlier indicated, we are not aware of any empirical study that has examined the relationship between credit risk and loan sizes in the context of the microfinance industry. By stark contrast, there is a large set of empirical studies that have been conducted on the traditional banking industry. For example, Jiménez and Saurina (2004), after analysing the Spanish banks, found that large loans carry lower risk, given that a borrower is normally a large firm and its operation is known in greater detail. Similarly, Berger and Udell (1990) and Booth (1992) reached the same conclusion. Related studies conducted by Berger and Udell (1995), Harhoff and Körting (1998) and Leeth and Scott (1989) documented a negative and statistically significant relationship between loan sizes and default risk.

Having discussed the traditional banking literature on the relationship between credit risk and loan sizes, we now turn to microfinance studies that have investigated the different factors that are influencing credit risk in the industry. The starting point of the review is a recent study by Lassoued (2017), who found that group lending methodology, and the high percentage of loans granted to women, significantly reduced the credit risk of 638 microfinance institutions, drawn from 87 countries over the period 2005–2015. Correspondingly, available evidence documented by Crabb and Keller (2006), Islam (1996), Morduch (1999) and Tchakoute-Tchuigoua and Nekhili (2012) arrived at the same conclusion; the three studies claimed that group lending mitigate risk by reducing an adverse selection and the problem of a moral hazard. Equally, a mounting body of empirical evidence demonstrate that targeting a female borrower is associated with high repayment rates and lower credit risks in the microfinance industry, for such evidence see: Agier and Szafarz (2013), D'Espallier et al. (2011), D'Espallier et al. (2013) and Strøm et al. (2014).

[3] Specifically, loan represents the microcredit, and the two are interchangeably used in this paper.

On a slightly different note, Djankov et al. (2007) and Porta et al. (1998) found evidence indicating that the legal system, creditor rights, and the enforcement quality promotes credit markets (Chikalipah, 2017b). Armendáriz de Aghion and Morduch (2000) underlined some apparatuses that reduce delinquencies from low-income borrowers without using group lending, which are small regular payments, provision of complimentary non-financial services, and a warning of non-refinancing options of the credit. Nkamnebe and Idemobi (2011) found that the low credit recovery in Nigeria is influenced by multidimensional factors, which are an endemic moral hazard in the credit market, lack of a skilled workforce to manage a credit portfolio, and rampant corruption across the country. While, Ayayi (2012) found that operational inefficiency negatively affects credit risk. Lastly, Krauss and Walter (2009) found no evidence of microfinance institutions being exposed to events in the international markets, and claimed that the financial performance of microfinance institutions is significantly correlated with domestic GDP growth.

Finally, as can be seen from the review of the literature in this section, the empirical investigation of the relationship between loan sizes and credit risks has mostly been performed on the traditional banking industry of the developed economies. By marked contrast, there is yet to emerge a study, in the context of microfinance, to investigate the association between loan sizes and credit risk. It is this gap in the research that warranted this empirical examination. The next section will present the theoretical model of credit risk and our estimation framework.

3. Model of credit risk and estimation strategy

3.1. Theoretical modelling of credit risk

Credit risk is an essential theme in banking and is of great concern to institutions, borrowers, and financial sector regulators (Pykhtin and Dev, 2002). Credit risk is the default situation, which transpires if the borrower is unable to meet the legal obligations laid out in the debt contract (Dimakos and Aas, 2004). A large body of literature in credit risk has been nurtured by both academics in finance, and practitioners in the financial services industry. The risk models have been developed based on the earlier work by Merton (1974) for corporate debt pricing. The model by Merton, assumes that a default event occurs at the maturity date of the debt if the assets value is less than the corresponding debt level. We also exploit the further extension of Merton's methodology by Black and Scholes (1973) for the financial option pricing.

The Black–Scholes–Merton methodology posits that the market value of the firm's underlying assets, which in the current context represents individual loans, follows the stochastic process

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad (1)$$

where V_A, dV_A are the firm's asset value and change in asset values, μ,σ_A are the firm's value drift rate and volatility, and dW denotes a Wiener process. Therefore, the probability of default can be expressed as

$$p_t = \text{pr}\left\{V_A^t \le X_t | V_A^0 = V_A\right\} = \text{pr}\left\{\text{In}\, V_A^t \le X_t | V_A^0 = V_A\right\} \quad (2)$$

where p_t is the probability of default in time t, V_A^t is the market value of the firm or individual assets at time t, and X_t is the book value of the loan obligation due at time t. The change in the value of the firm's assets is described in Eq. (1), and accordingly the value at time t is V_A^t, considering that the value at time 0 is V_A, thus

$$\text{InV}_A^t = \text{InV}_A + \left[\mu - \frac{\sigma_A^2}{2}\right] t + \sigma_A\sqrt{t\varepsilon} \quad (3)$$

where μ is the expected return on the firm's asset and ε is the random component of the firm's return. If Eqs. (2) and (3) are amalgamated, the probability of default can be expressed as

$$p_t = \text{pr}\left\{\text{In}V_A + \left[\mu - \frac{\sigma_A^2}{2}\right] t + \sigma_A\sqrt{t\varepsilon \le X_t}\right\} \quad (4)$$

If we rearrange Eq. (4) we end up with

$$p_t = \text{pr}\left\{-\frac{\text{In}\frac{V_A}{X_t} + \left[\mu - \frac{\sigma_A^2}{2}\right] t}{\sigma_{A\sqrt{t}}} \ge \varepsilon\right\} \quad (5)$$

The Black–Scholes–Merton methodology's proposition is that the random component of the firm's asset return is normally distributed, $\varepsilon \sim N(0, 1)$ and if Eq. (5) is defined in terms of the cumulative normal distribution, then we get

$$p_t = N\left\{-\frac{\text{In}\frac{V_A}{X_t} + \left[\mu - \frac{\sigma_A^2}{2}\right] t}{\sigma_{A\sqrt{t}}}\right\} \quad (6)$$

Having discussed the probability of default using the Black–Scholes and Merton approaches, we further outlined two assumptions that could potentially prompt loan defaults in the context of the microfinance industry.

Firstly we assume that microcredit borrowers have an incentive to default if the debt obligation outweighs their social standing in the community. This assumption is premised on the fact that social capital act as collateral in the microfinance industry. It is for this reason that there have been reports of microcredit borrowers committing suicide in the event that they fail to repay their contracted loans (Mader, 2013).

Secondly, we also assume that the incentive to default might be conditional on the loan amount, especially with individual loans. If the verification and enforcement costs surpass the outstanding loan balance, then it is not optimal, on the side of the microfinance institutions, to institute debt recovery procedures. Thus, the microcredit borrowers might have the motive to default. It is on this scenario that the notion that providing small uncollaterised loans is characteristically risky is premised on (de Quidt et al., 2016; Emekter et al., 2015).

3.2. Estimation strategy

To investigate the effect of loan sizes on credit risk in the microfinance industry in SSA, we exploit the GMM estimator as the estimating method of our data. Given that our panel dataset has a small $\boldsymbol{T}$ and large $\boldsymbol{N}$, meaning the short time dimension of a 19 year-period and a large cross-section dimension incorporating 632 MFIs, the best estimation method suitable for such a sample is the system GMM estimator (Windmeijer, 2005). The system GMM econometric specification is more asymptotically efficient, robust and is a more reliable estimator in terms of power and error type-I (Windmeijer, 2005). Therefore, we apply the Blundell–Bond system GMM estimator (Blundell and Bond, 2000), and it carries the following form

$$Y_{i,j,t} = \boldsymbol{\delta} Y_{i,j,t-1} + \sum_{l=1}^{L} \lambda' X_{i,j,t} + \varepsilon_{i,j,t} \tag{7}$$

The assumptions of Eq. (7) are

$$i = 1, \ldots\ldots\ldots, n, \quad t = 1, \ldots\ldots\ldots, T_j,$$

$$\varepsilon_{i,j,t} = \upsilon_i + \gamma_t + \mu_{i,j,t}$$

where i indexes the MFI and j country, while t is year. The dependent variable is denoted by $Y_{i,j,t}$, which is the logarithm (log) of credit risk faced by the MFI i in country j and in year t; at the same time $Y_{i,j,t-1}$ is the one period lag of the log of credit risk, with $\boldsymbol{\delta}$ being the speed of adjustment to equilibrium. Equally, $X_{i,j,t}$ depicts a vector of explanatory variables (which are female borrowers, firm size, lending methodology, lending interest rates and loan sizes) of the MFI i in country j and in year t. Whereas, the $\varepsilon_{i,j,t} = \upsilon_i + \gamma_t + \mu_{i,j,t}$ is the disturbance, γ_t are the unobservable time effects, υ_i is the unobserved complete set of the MFI-specific effects, and, $\mu_{i,j,t}$ is the idiosyncratic error. The estimation framework specified in Eq. (7) is a two-way error component regression model, where $\upsilon_i \sim \left[IIN\left(0, 0, \sigma_\upsilon^2\right)\right]$ and is independent of $\mu_{i,t} \sim \left[IIN\left(0, \sigma_\mu^2\right)\right]$.

The GMM is an efficient estimation technique and has several advantages. To begin with, (i) the GMM estimator permit a contemporaneous study of the possibility of conditional convergence ($\boldsymbol{\delta}$) or the speed of adjustment to equilibrium. Specifically, a statistically significant value of between 0 and −1 of the lagged dependent variable would imply that any shock to the credit risk of MFIs would persist, but revert to the normal level (Dietrich and Wanzenried, 2011). On top of that, (ii) the GMM estimator is accommodative in identifying the sources of endogeneity and accounting for heteroskedasticity in the data (Hsiao, 2014; Windmeijer, 2005). In that respect, the GMM approach provides a resourceful tool to deal with possible endogeneity between credit risk and the two exogenous variables (loan sizes and lending interest rates). Thirdly and lastly, the GMM estimator offers a rationally robust solution to the problem of possible model misspecification (Arellano and Bover, 1995; Blundell and Bond, 1998).

When estimating Eq. (7), a two-step system GMM is preferred against a one-step, considering that its standard errors are asymptotically robust to heteroscedasticity and are more efficient (Blundell and Bond, 1998; Roodman, 2009). The dynamic two-step system GMM estimator is supported by the fixed effect (within group) estimator. In addition, the fixed effects estimates verifies the consistency and accuracy of our GMM estimates. Thus, the fixed effect via OLS regression is of the form

$$\boldsymbol{Y}_{i,j,t} = \boldsymbol{\delta Y}_{i,j,t-1} + \sum_{l=1}^{L} \lambda' \boldsymbol{X}_{i,j,t} + \eta_i + \omega_{i,j,t} \tag{8}$$

where i indexes MFI, j country, t is year, $\boldsymbol{Y}$ is the dependent variable, $\boldsymbol{X}$ is a vector of explanatory variables shown in Table 2, $\boldsymbol{\delta}$ being the speed of adjustment to equilibrium, η_i represents unobserved MFI-specific effects, and $\omega_{i,j,t}$ is the idiosyncratic error.

Finally, a vector of our explanatory variables represented by $\boldsymbol{X}_{i,j,t}$ also include: (i) year dummies, and (ii) dummies for countries. The two dummy variables control for unobserved country characteristics and event shocks that could have happened during the study period. The next section presents the data, summary statistics and the strategy of selecting the optimal lag length of our dependent variable.

Table 1
List of countries in the sample.

1. Angola	11. Cote d'Ivoire	21. Malawi	31. South Sudan
2. Benin	12. Ethiopia	22. Mali	32. Swaziland
3. Burkina Faso	13. Gabon	23. Mozambique	33. Tanzania
4. Burundi	14. Gambia, The	24. Namibia	34. Togo
5. Cameroon	15. Ghana	25. Niger	35. Uganda
6. **CAR**	16. Guinea	26. Nigeria	36. Zambia
7. Chad	17. Guinea-Bissau	27. Rwanda	37. Zimbabwe
8. Comoros	18. Kenya	28. Senegal	
9. Congo, **DR**	19. Liberia	29. Sierra Leone	
10. Congo, **Rep**	20. Madagascar	30. South Africa	

Notes: Table 1 lists the 37 countries of the sub-Saharan African region included in our analysis. These countries housed the 632 microfinance institutions sampled in this study. The acronym **CAR** abbreviates the Central Africa Republic. Whereas the letters **DR** signifies the Democratic Republic, and **Rep** shortens the word Republic.

4. Data and summary statistics

4.1. Description of the data

This study benefits from data obtained from the Microfinance Information eXchange (MIX). The MIX market is the oldest and largest data depository in the microfinance industry, with over 1800 MFIs reporting data to the organisation.[4] Our full unbalanced sample comprises of data from 632 microfinance institutions drawn from 37 countries of the SSA region, and covers the period from 1995 to 2013. Table 1 provides the complete list of countries of the SSA region included in our analysis. Appendix A provides further details on the distribution of the 632 MFIs into 37 countries sampled for this study.

[4] There are other emerging depositories of microfinance data; some include FINCA International, MicroRate, Oikocredit, and Rabobank foundation.

Table 2
Descriptive statistics.

	Countries = 37		MFIs = 632		Period = 1995–2013	
	N	Mean	S.D	Min	Median	Max
Credit risk	1363	0.10	0.13	0.00	0.05	0.97
Female borrowers	1363	0.61	0.26	0.01	0.61	1.00
Firm size (USD in millions)	1363	22.80	137.0	0.001	2.03	3160
Lending methodology	1309	340.5	371.3	5.0	251.0	4637.0
Lending interest rates	1363	0.27	0.22	-0.3	0.22	2.02
Loan sizes (USD)	1363	593.20	1141.6	40.0	247.00	22252.0

Notes: Table 2 reports the summary statistics {number of observations (*N*), mean, standard deviation (S.D), minimum (MIN), median and maximum (MAX)} for our dependent and explanatory variables that enter our estimation frameworks. The data is in levels. The dataset covers the period 1995–2013, and incorporates 632 microfinance institutions drawn from 37 countries of the SSA region shown in Table 1. The efficiency (cost per customer) and loan size variables are dollarised, using the United States Dollars (USD) official exchange rate at the financial year-end.

The dependent variable entering our estimation frameworks is credit risk, and is captured using portfolio at risk (PAR) over 90 days. This proxy is a widely used measure of credit risk in the microfinance literature (see for example: Abdullah and Quayes, 2016; Agier and Szafarz, 2013; Chikalipah, 2017a,b; D'Espallier et al., 2011). The credit risk variable can be expressed as

$$Y_{i,t} = \frac{\sum_{i} OL_{i,t}}{\sum_{i=1} GLP_{i,t}} \tag{9}$$

where $Y_{i,t}$ denotes the portfolio at risk, which is the credit risk of MFI i in time$t$; $OL_{i,t}$ is the total outstanding loans over 90 days of a microfinance institution i in time t, and $GLP_{i,t}$ is the gross loan portfolio of a microfinance institution i in time t.

The explanatory variables entering our estimation frameworks are defined as follows. First, the variable of interest is the average loan sizes of each of the respective microfinance institutions sampled in this study. Moreover, it is a popular belief, in the microfinance literature, that small loan amounts are principally targeted at poor people (Cull et al., 2007; Hermes and Lensink, 2011; Hermes et al., 2011; Mersland and Strøm, 2010).[5] The loan sizes are monetary terms, and dollarised (USD) using the official exchange rate at the respective financial year-end. Second, is the percentage of female borrowers; captured as a number of active female borrowers divided by the aggregate number of active borrowers for each microfinance institution in a given year. Third, the firm size of MFIs represents the total assets of the MFIs at the end of a financial year. Fourth, the lending methodology is captured using the number of active borrowers per loan officer. This variable simultaneously captures: (i) the efficiency of MFIs, which is premised on the assumption that a high number of borrowers per loan officer could imply an optimal use of personnel; and (ii) that an elevated number of borrowers per loan officer could also indicate the use of group lending.[6]

The fifth and final control variable entering our estimation model is microcredit interest rates captured using the portfolio yield proxy. The portfolio yield, as a proxy for lending interest rates, is a commonly used measure in the microfinance literature (Ahlin et al., 2011; Cotler and Almazan, 2013; Cull et al., 2007; Dorfleitner et al., 2013; Roberts, 2013; Tchakoute-Tchuigoua, 2012, 2014). According to the MIX market portfolio, yield is constructed using the following equation form

$$PY_{i,t} = \frac{\sum_{i} [R + FEC]_{i,t}}{\sum_{i=1} GLP_{i,t}} \tag{10}$$

where $PY_{i,t}$ is the portfolio yield of MFI i in period t, $R_{i,t}$ is the total interest income and $FEC_{i,t}$ is the total additional loan-related fees and commission received from borrowers by the MFI i in period t, whereas $GLP_{i,t}$ is the average gross loan portfolio of MFI i in period t. The average gross loan portfolio is calculated by totalling the gross loan portfolio at the beginning and end of a financial year, and the total is then divided by two. The main advantage of using the microcredit interest rates measure, outlined in Eq. (10), is that it captures any additional loan-related costs besides the agreed interest on the loan.

In order to geometrically adjust inflation from the $PY_{i,t}$ in Eq. (10), the following formula is applied

$$PY_{i,t} = \left\{ \frac{(1 + PY_{i,t})}{[1 + CPI_{i,j}]} \right\} - 1 \tag{11}$$

where $CPI_{i,j}$ abbreviates the consumer price index, which is inflation in country j and in period t. Consequently, the microcredit interest rates ($PY_{i,t}$) entering our estimation model are all inflation adjusted.

4.2. Summary statistics

Table 2 presents the summary statistics of the dependent and explanatory variables. On average, the credit risk faced by 632 MFIs in our sample was 10% over the period from 1995 to 2013. The difference between the mean and the median shows that there were small credit risk variances among the MFIs in our sample, in the period considered in this study. The average percentage of female borrowers in our sample is 61%. Whereas, the number of borrowers per loan officer averaged 340, with the lowest being 5 borrowers per loan officer, and the highest of

[5] Moreover, this assumption is solidified by the fact that 50% (Median) of loan sizes in our sample are below USD 250, with an average (Mean) of below USD 600.

[6] We do not have information about the lending methodology employed by the 632 microfinance institutions sampled in this paper.

Table 3
Selecting optimal lag length of credit risk.

	Dependent variable: log credit risk	
	OLS (With Robust SE) (1)	OLS (With Robust SE) (2)
Lagged log credit risk $_{(t-1)}$	−0.203*** (0.054)	
Lagged log credit risk $_{(t-2)}$	−0.078 (0.066)	−0.065 (0.067)
Lagged log credit risk $_{(t-3)}$	−0.012 (0.055)	0.016 (0.054)
Log female borrowers	−0.071*** (0.016)	−0.048*** (0.007)
Log firm size	2.740 (1.834)	2.526 (2.762)
Log lending methodology	−0.013*** (0.005)	−0.014*** (0.006)
Log lending interest rates	0.385** (0.189)	0.127*** (0.055)
Log loan sizes	0.011*** (0.003)	0.098*** (0.043)
R^2	0.401	0.385

Notes: Table 3 reports the number of lags of credit risks among the MFIs operating in the SSA region that are statistically significant. The results are obtained after estimating Eq. (12) on a sample of 632 microfinance institutions operating in 37 countries listed in Table 1. The sample used covers the period from 1995 to 2013, and the dependent variable is the log of credit risk. The figures in parentheses represent robust standard errors (SEs). The symbol * expresses significance at the 10% level, ** at 5% and *** at 1% level. All estimations included dummies for each country and time.

slightly over 4600 borrowers per loan officer. The average firm size (total assets) of the 632 MFIs sampled in this study is USD 22.80 million, with the smallest MFI posting assets valued at USD 1000 in the period considered in this study, and the largest MFIs posted assets valued at USD 3.16 billion. In terms of loan size, the average was about USD 590, with the smallest loan amount of USD 40 and largest of slightly over USD 22,200. There was not much of a huge difference between the mean and median of the loan sizes between 1995 and 2013. Finally, the microcredit interest among the 632 MFIs averaged 27% in the study period. The lowest lending interest rate in the same underlying period was a negative 3% and the highest of 202%. It is possible to have negative interest rates given that our lending interest rates are inflation adjusted, as indicated in Eqs. (10) and (11).

4.3. Optimal lag length of credit risk

In our estimation models we only considered one period lag of the credit risk variable, and we reasoned that microcredit has a short maturity period; often the maturity ranges from 6 months to 12 months. In light of this, a one period lag of credit risk is enough to capture all the influences of the past on the present. To evaluate if a one period lag is enough to capture the dynamics of credit risk, we fitted an Ordinary Least Squares (OLS) regression on the current credit risk on the three lags of itself and controlled for MFI-specific attributes. This approach follows Wintoki et al. (2012) methodology. The OLS regression is of the form

$$Y_{i,j,t} = \alpha_1 + \sum_{k=1}^{k=3} Y_{i,j,t-k} + \sum_{l=1}^{L} \lambda' X_{i,j,t} + \omega_{i,j,t} \tag{12}$$

where i indexes the MFI and j country, while t is year. The dependent variable is denoted by $Y_{i,j,t}$, which is the log of credit risk faced by the MFI i in country j and in year t; at the same time $Y_{i,j,t-k}$ are the lagged periods of credit risk, with k being the number of lags. Equally, $X_{i,j,t}$ depicts a vector of our explanatory variables given in Table 2, with $\omega_{i,j,t}$ being the idiosyncratic error.

The results of estimating Eq. (12) are displayed in Table 3. In column 1 the coefficients of a one period lag is statistically significant at 1%, whereas the coefficients of the 2nd and 3rd lags are insignificant. Likewise, in column 2, we dropped the one period lag and included the 2nd and 3rd lags, and in this specification both the 2nd and 3rd lags are statistically insignificant. This confirms that including a one period lag in our estimation framework is sufficient to capture the dynamic aspect of credit risk in the microfinance industry of the SSA region.

5. Main empirical results

In this section, we examine the empirical relationship between credit risk and loan sizes. To do so, we employee two estimators: (i) the dynamic two-step system GMM, and (ii) the fixed effects. As previously indicated, the fixed effect estimator is used to check the consistency of our preferred GMM estimates. Overall, the estimates shown in Table 4 are consistent, robust, and indicate the goodness of fit of the system GMM estimator. Exactly, the results of the Hansen tests, of over-identifying restrictions, yield p-values of 1.0, and as such, we cannot reject the hypothesis that our instruments are valid. Also, the results of the specification test, which are the Arellano–Bond tests AR (2) second-order serial correlation tests, reveal p-values of 0.7. This means that we cannot reject the null hypothesis of no second-order serial correlation. Finally, taken together, the magnitudes of the estimates given in Table 4 appear reasonable.

We also report the results of the difference-in-Hansen test of exogeneity in Table 4. The null hypothesis for this test is that the additional subset of instruments, used in the dynamic system GMM estimator in levels, is exogenous (Eichenbaum et al., 1988). The results of the difference-in-Hansen test of exogeneity show a p-value of 0.401. This indicates that we cannot reject the hypothesis that the additional subset of instruments employed, when estimating the dynamic system GMM estimator in levels, is exogenous.

Table 4
Effect of loan sizes on credit risk: baseline estimation results.

	Dependent variable: log credit risk	
	Fixed effects (Within Group)	Two-step system GMM
Lagged log credit risk	−0.149*** (0.022)	−0.152*** (0.029)
Log female borrowers	−0.278*** (0.105)	−0.399*** (0.061)
Log firm size	0.042 (0.078)	−0.118*** (0.028)
Log lending methodology	−0.009*** (0.004)	−0.007*** (0.002)
Log lending interest rates	0.068*** (0.018)	0.061*** (0.024)
Log loan sizes	0.314** (0.149)	0.387*** (0.165)
Observations	608	608
R-squared (within)	0.276	
Number of instruments		158
AB test AR (1) *p*-value		0.000
AB test AR (2) *p*-value		0.680
Hansen test *p*-value		0.979
DiH test of exogeneity *p*-value		0.401

Notes: Table 4 reports the results from the FE and system GMM estimations of the effect of loan sizes on credit risks of microfinance institutions operating in the SSA region. The sample covers the period from 1995 to 2013, and the dependent variable is the log of credit risk. The figures in parentheses represent standard errors (SEs). The symbol * expresses significance at the 10% level, ** at 5% and *** at 1% level. The two-step system GMM procedure follows Blundell and Bond (2000), and the Hansen test is the test for over-identifying restrictions in the GMM model. Additionally, the null under the Hansen test is that all instruments are valid. The Arellano–Bond (AR) tests the serial correlation in the first differenced residuals, under the null of no serial correlation. Thus, the AR (1) and AR (2) refer to the Arellano–Bond first and second-order serial correlation tests. The Diff-in-Hansen (**DiH**) test of exogeneity is under the null that instruments used for the equations in levels are exogenous. All estimations included dummies for each country and time.

From the results reported in Table 4, the starting point of our discussion is the coefficient of the lagged dependent variable (log credit risk). The coefficients are negative and statistically significant at 1%. To briefly recap, the lagged log credit risk measures the speed of adjustment to equilibrium($\boldsymbol{\delta}$), or conditional convergence (Hsiao, 2014). Specifically, the coefficients indicate that credit risk is persistent in the microfinance industry in SSA, and reverts to the long-run equilibrium at a speed of about 15% per annum. Moreover, the negative and statistically significant coefficients of a lagged dependent variable re-enforces the appropriateness of employing the system GMM estimator as our main estimation technique.

We next interpret the estimated coefficient of the log of loan sizes, and in all of the specifications of Table 4 the estimates are positive and significant at 1%. This suggests that a 1% increase in loan size is associated with a 0.3–0.4% increase in credit risk. In other words, small loans are less risky in the microfinance industry of the SSA region. This finding is at odds with the widely held anecdotal viewpoint that providing small uncollaterised microcredit loans is inherently a risk (see for instance: Al-Azzam and Mimouni, 2017). And also stands in contrast with the traditional banking literature (for evidence, see: Ali and Daly, 2010; Berger and Udell, 1990, 1995; Booth, 1992; Harhoff and Körting, 1998; Jiménez and Saurina, 2004; Leeth and Scott, 1989).

Notwithstanding that, our results could plausibly be explained as follows. First, the findings could point to the importance of social capital among microcredit borrowers. The social standing of borrowers, to a large part, plays a significant role in repaying the contracted credit. This can also be confirmed by a series of suicides by borrowers that are precipitated by the failure to meet the debt obligations (Mader, 2013). Second, this could indicate the close relationship between the loan officers and the microcredit borrowers; field loan officers go around their assigned constituencies to collect loan repayments. This close relationship between the microcredit borrowers and the loan officers overcomes the information asymmetry. Thirdly and lastly, our results could also indicate that the poor are honest borrowers and they do pay back the contracted loans. Moreover, similar findings were reached by Carruthers et al. (2012) and Yunus (1999).

The coefficient of log lending interest rates, as expected, is positive and significant at 1%. The results indicate that a 1% increase in microcredit interest rates is related to a 0.06–0.07% increase in credit risk. The size of the coefficient infers a marginal effect of lending interest rates on credit risk, which is consistent with prior empirical findings (Ayayi, 2012; Nkamnebe and Idemobi, 2011). The coefficient of female borrowers is negative and statistically significant at 1% level. This indicates that female borrowers are associated with low risk in the microfinance industry in the SSA. This is consistent with the microfinance literature (see, inter alia: Agier and Szafarz, 2013; D'Espallier et al., 2011, 2013; Strøm et al., 2014).

Turning to the coefficient of firm size, the GMM estimates demonstrate that there exists a negative and statistically significant relationship between credit risk and firm size. The result implies that large MFIs face a low credit risk compared to small firms. The plausible explanation of our finding is the learning effect; larger MFIs understand the credit market better compared to newly established and small firms. Another possible explanation is that large MFIs have enough resources to invest in systems that evaluate the credit worthiness of customers, and thus, there have low default rates. The coefficient of a lending methodology is negative and significant at 1% in both estimators, albeit the impact is rather small. The results show that operational efficiency and group lending is negatively associated with credit risk in the microfinance industry of the SSA

Table 5
Effect of loan sizes on credit risk: further estimation results.

	Dependent variable: log credit risk	
	Fixed effects (Within Group)	Two-step system GMM
Lagged log credit risk	−0.180*** (0.018)	−0.188*** (0.025)
Log loan sizes	0.248*** (0.106)	0.307*** (0.132)
Observations	1083	1083
R-squared (within)	0.319	
Number of instruments		102
AB test AR (1) *p*-value		0.084
AB test AR (2) *p*-value		0.618
Hansen test *p*-value		0.783
DiH test of exogeneity *p*-value		0.115

Notes: Table 5 reports the results from the FE and system GMM estimations of the effect of loan sizes on credit risks of microfinance institutions operating in the SSA region. The sample covers the period from 1995 to 2013, and the dependent variable is the log of credit risk. The figures in parentheses represent standard errors (SEs). The symbol * expresses significance at the 10% level, ** at 5% and *** at 1% level. The two-step system GMM procedure follows Blundell and Bond (2000), and the Hansen test is the test for over-identifying restrictions in the GMM model. Additionally, the null under the Hansen test is that all instruments are valid. The Arellano–Bond (AR) tests the serial correlation in the first differenced residuals, under the null of no serial correlation. Thus, the AR (1) and AR (2) refer to the Arellano–Bond first and second-order serial correlation tests. The Diff-in-Hansen (**DiH**) test of exogeneity is under the null that instruments used for the equations in levels are exogenous. All estimations included dummies for each country and time.

Table 6
Effect of loan sizes on credit risk using winsorized variables.

	Dependent variable: log credit risk	
	Fixed effects (Within Group)	Two-step system GMM
Lagged log credit risk	−0.196*** (0.034)	−0.205*** (0.046)
Log female borrowers	−0.215*** (0.083)	−0.465*** (0.131)
Log firm size	0.086 (0.081)	−0.102*** (0.017)
Log lending methodology	−0.018*** (0.007)	−0.021*** (0.010)
Log lending interest rates	0.118*** (0.047)	0.132*** (0.055)
Log loan sizes	0.354*** (0.111)	0.317*** (0.091)
Observations	608	608
R-squared (within)	0.301	
Number of instruments		158
AB test AR (1) *p*-value		0.134
AB test AR (2) *p*-value		0.399
Hansen test *p*-value		0.641
DiH test of exogeneity *p*-value		0.211

Notes: Table 6 reports the results from the FE and system GMM estimations of the effect of loan sizes on credit risks of microfinance institutions operating in the SSA region. All variables are Winsorized at a 5% level. The sample covers the period from 1995 to 2013, and the dependent variable is the log of credit risk. The figures in parentheses represent standard errors (SEs). The symbol * expresses significance at the 10% level, ** at 5% and *** at 1% level. The two-step system GMM procedure follows Blundell and Bond (2000), and the Hansen test is the test for over-identifying restrictions in the GMM model. Additionally, the null under the Hansen test is that all instruments are valid. The Arellano–Bond (AR) tests the serial correlation in the first differenced residuals, under the null of no serial correlation. Thus, the AR (1) and AR (2) refer to the Arellano–Bond first and second-order serial correlation tests. The Diff-in-Hansen (**DiH**) test of exogeneity is under the null that instruments used for the equations in levels are exogenous. All estimations included dummies for each country and time.

region. This is consistent with prior empirical findings reported by Crabb and Keller (2006), Islam (1996), Morduch (1999) and Tchakoute-Tchuigoua and Nekhili (2012).

In a nutshell, we conclude that there is a large, relatively accurate and significant effect of loan sizes on the credit risk of microfinance institutions operating in the SSA region. The next section presents further results to fortify the baseline estimates reported in Table 4.

6. Robustness checks

6.1. Further results from robustness checks

In this sub-section, we provide further results and robustness checks of our baseline estimates reported in the previous section. The estimation results are useful for comparing the estimates given in Table 4 – in the previous section. A possible concern with the results, reported in the previous section, is that our baseline estimates are biased and fragile to different estimation techniques. To address these concerns we perform the following procedures to verify the robustness and stability of our baseline results.

We first re-estimated Eqs. (7) and (8), without the control variables, while keeping the sample size constant, and the estimates were similar, and this implies that the effect of loan sizes on credit risk does not work through our control variables. The results of using this approach are shown in Table 5. Generally, the estimates are consistent, despite the magnitudes of the coefficients being different. Precisely, when matching the results reported in Tables 4 and 5, the coefficients of a one period lag of credit risk (in logs) are slightly large, whereas the coefficients of log loan sizes are somewhat smaller. However, this does not distort our initial results, and it is fair to conclude our results are not biased by other possible factors that influence credit risk.

Secondly, the empirical results, reported in Tables 4 and 5, do not consider the possible influence of outliers on the outcome of our results. Specifically, the outliers are extreme values in our data. Statistically, it is important to address the possible effect of outliers in the data, considering that they might cause bias in the estimates (Barnett and Lewis, 1994). To address this concern, we applied the Cook's Distance method of identifying outliers in the data (Cook, 1977). See Appendix B for the equation form of Cook's Distance methodology. The results of Cook's Distance identified 51 observations as an outlier; those that were away from the Cook's Distance mean a threshold value of 3. Instead of dropping these observations from our sample, we opted for statistical transformation of our variables using the Winsorization approach, at a 5% level.

The results obtained after estimating Eq. (7) and (8) using the Winsorized variables are presented in Table 6. Overall, our estimates are consistent and robustly significant, even though the magnitudes of the coefficients are marginally different from the baseline results reported in Table 4. Therefore, we can also reasonably infer that the outliers in our sample do not bias our results.

6.2. *Evaluating the strength of the instrument set of GMM estimator*

In this sub-section we examine the validity of the instruments used in our GMM estimates. To achieve that, we adopt a methodology proposed by Staiger and Stock (1997) and Stock and Yogo (2005). The technique involves estimating the following two-stage least squares (2SLS) regressions

$$\boldsymbol{Y}_{i,j,t} = \alpha_l + \beta_l \boldsymbol{X}_{i,j,t} + \omega_{i,j,t} \tag{13}$$

$$\Delta Y_{i,j,t} = \alpha_d + \beta_d \Delta \boldsymbol{X}_{i,j,t} + \omega_{i,j,t} \tag{14}$$

where i indexes MFI, j country, t is year, $\boldsymbol{Y}$ is the dependent variable, $\boldsymbol{X}$ is a vector of explanatory variables shown in Table 2 and $\omega_{i,j,t}$ is the idiosyncratic error. The variables entering Eq. (13) are in levels and in Eq. (14) are first-differenced. Thus, to evaluate the validity of the instruments, we obtain the F-statistics by regressing each variable on all lagged differences used as instruments in the level equation. Equally, for variables in differences, we obtain F-statistics by regressing each variable on all lagged levels used as instruments in the differenced equation.

Table 7 shows the F-statistics for all the first-stage regressions, and the results are significant, which indicates that the instruments used in our GMM estimates are valid. This implies that the explanatory variables that entered our estimation frameworks have strong explanatory power. According to Staiger and Stock (1997), the rule of the thumb is that the F-statistics of the instruments must be greater than 10.0 to signify a significant explanatory power. In other words, this implies the strength of the instruments (Stock and Yogo, 2005).

Table 7
Identification of weak instruments.

Panel A: data in levels			
	F-Statistic	p-value	R^2
Log female borrowers	98.83	0.000	0.231
Log firm size	69.47	0.000	0.163
Log lending methodology	12.91	0.001	0.033
Log lending interest rates	25.70	0.000	0.049
Log loan sizes	75.92	0.000	0.172
Panel B: data in first-diff			
	F-Statistic	p-value	R^2
ΔLog female borrowers	39.11	0.002	0.082
ΔLog firm size	20.46	0.000	0.049
ΔLog lending methodology	19.44	0.000	0.036
ΔLog lending interest rates	18.330	0.000	0.002
ΔLog loan sizes	14.320	0.001	0.003

Notes: Table 7 presents the F-statistics, p-values and R^2 of fitting OLS first-stage regressions of levels and first-differenced variables. Additionally, the results in Panels A and B are obtained after estimating Eqs. (13) and (14), respectively. All estimations included dummies for each country and time. The comparable critical values (CV) for instrument are taken from Staiger and Stock (1997), and Stock and Yogo (2005).

7. Summary and concluding remarks

There is a consensus in the empirical literature that smaller loans carry a higher default risk, and the exact opposite is true for large loans. Albeit these findings were arrived at after testing the data of traditional banks domiciled in the developed economies. This study investigated these claims by estimating the effect of loan sizes on credit risk in the microfinance industry of the sub-Saharan African region. The main innovation in our approach is to exploit the traditional banking methodologies and apply them to the microfinance industry. Doing so contributes to the understanding of credit risk modelling in the microfinance industry.

We used a sample that comprised of over 1300 annual observations, and 632 microfinance institutions drawn from 37 countries of the sub-Saharan African (SSA) region, over the period 1995–2013. Using the GMM and fixed effects estimators, our results indicate that credit risks are positively related to loan sizes among microfinance institutions operating in SSA. Succinctly, contrary to a widely held narrative, our findings indicate that small loans carry lower risk relative to larger amounts. This re-enforces the notion that the poor are honest and do pay back the contracted loan obligations. In addition to the academic interest, we believe that the findings of this study may be of use to the credit portfolio managers of microfinance institutions operating in the SSA region.

We view our paper as being the first to provide empirical evidence on the relationship between loan sizes and credit risk in the context of the microfinance industry of the SSA region. Thus, there is one research directive that is most interesting and important. Future research must strive to shed more light on the relationship between credit risks and the loan sizes of microfinance institutions, which predominantly use the platform of mobile money services.

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Appendix A.

Table A1.

Table A1
Microfinance institutions per country in the sample.

Country	MFIs
1. Angola	2
2. Benin	28
3. Burkina Faso	17
4. Burundi	12
5. Cameroon	27
6. Central African Republic	1
7. Chad	3
8. Comoros	3
9. Congo, Democratic Republic of the	24
10. Congo, Republic of the	5
11. Cote d'Ivoire (Ivory Coast)	27
12. Ethiopia	23
13. Gabon	1
14. Gambia, The	2
15. Ghana	78
16. Guinea	8
17. Guinea-Bissau	4
18. Kenya	38
19. Liberia	3
20. Madagascar	15
21. Malawi	9
22. Mali	22
23. Mozambique	11
24. Namibia	2
25. Niger	12
26. Nigeria	75
27. Rwanda	22
28. Senegal	30
29. Sierra Leone	13
30. South Africa	17
31. South Sudan	4
32. Swaziland	1
33. Tanzania	23
34. Togo	24
35. Uganda	29
36. Zambia	10
37. Zimbabwe	7

Notes: Table A1 reports the distribution of the 632 Microfinance Institutions in our sample into the 37 countries of the sub-Saharan African region.

Appendix B.

The Cook's Distance method

The Cook's Distance estimation technique, also known as Cook's D, was founded by Cook (1977). The method is commonly performed after running an ordinary least squares regression analysis. The equation form of Cook's Distance is expressed as

$$D_i = \frac{\sum_{j=1}^{n} (\hat{Y}_i - \hat{Y}_{j(i)})^2}{pMSE} \tag{B.1}$$

The subsequent equation is equally expressed as

$$D_i = \frac{e_i^2}{pMSE}\left[\frac{h_{ii}}{(1-h_{ii})^2}\right] \tag{B.2}$$

$$D_i = \frac{(\hat{\beta} - \hat{\beta}^{-i})^T (X^T X)(\hat{\beta} - \hat{\beta}^{-i})}{(1+p)s^2} \tag{B.3}$$

where $\hat{\beta}$ is the least squares (LS) estimates of β, and $\hat{\beta}^{-i}$ is the LS estimate of β on the dataset without case i. While $\hat{Y}_j$ is the prediction from the full regression model for observation j; $\hat{Y}_{j(i)}$ is the prediction for observation j from a refitted regression model in which observation i has been omitted. h_{ii} is the ith diagonal element of the hat matrix $X(X^2X)^{-1}X^T$. The letters MSE represents the Mean Square Errors, and p is the number of fitted variables.

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