Advances in Management & Applied Economics, vol. 4, no.2, 2014, 81-90
ISSN: 1792-7544 (print version), 1792-7552(online)
Scienpress Ltd, 2014

The Female Superiority in Loan Repayment Hypothesis: Is it Valid in Ghana?

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Abstract

The paper subjects the female superiority in loan repayment hypothesis to empirical scrutiny with data from the microfinance industry in Ghana. Using binary logistic regression, our data provide evidence that females are more likely to default on their loans than males which presupposes that males are rather better borrowers. The paper, therefore, submits that the female superiority in loan repayment hypothesis may not be valid in Ghana.

JEL classification numbers: D20, G21, G23, N20
Keywords: Female, Male, Loan Default, Microfinance, Microcredit

1 Introduction

In credit management, default occurs when a borrower fails to meet debt obligations. It could be an inability to meet a scheduled payment or a violation of a covenant (condition) of the debt contract. This implies that default can take two forms: service default and technical default. Service default refers to failure to repay a loan whilst technical default refers to a violation of a condition of the loan (Klein, 2006).

Default in lending is inevitable. However, it can be controlled within acceptable limits. This explains why lending institutions usually institute credit risk management standards. The ultimate aim of credit risk management is to minimize as much as possible the rate of loan default in order to ensure sustainability and profitability in the lending business.

Microfinance institutions (MFIs) as providers of credit to the poor and financially excluded in society are usually saddled with the herculean task of minimizing loan default rates because of the economic status of their clients. However, group lending methodology is hailed for its ability to mitigate the incidence of high loan default rates in

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Article Info: *Received* : December 12, 2013. *Revised* : January 21, 2014.
Published online : April 10, 2014

micro-lending. It makes all group members responsible for the repayment of the loan, and thus, provides incentives for individual group members to screen and monitor the other members of the group and to enforce repayment (Hermes *et al.*, 2005). However, not all micro-lending is done through group approach. Individual lending still remains a significant feature of microfinance operations despite its hackneyed shortfalls. Another prescription for dealing with credit risk in microfinance is lending more to females since they are less likely to default (D'Espallier et al., 2009; The World Bank, 2007; Dyar *et al.*, 2006). However, the female superiority in loan repayment hypothesis is yet to garner universal acceptance because some studies have failed to confirm it (Adusei and Appiah, 2011; Godquin, 2004; Bhatt & Tang, 2002). Adusei and Appiah (2011) use data from the credit union industry in Ghana to test this hypothesis and provide evidence to the effect that females are not better borrowers. The current study also tests this hypothesis with a different dataset from Ghana and confirms the evidence from the Adusei and Appiah's (2011) study that females are not better borrowers.

The rest of the paper is organized as follows. The next section of the paper reviews literature and develops appropriate hypotheses. This is followed by the methodology section. Next in line is the results section. The conclusion and policy implications section ends the paper.

2 Review of Related Literature

Microfinance, the provision of financial and non-financial services to the poor and financially excluded, has received a lot of attention in Ghana probably due to its socio-economic relevance (Adusei, 2013; Adusei and Appiah, 2012; Adusei and Appiah, 2011; Aboagye, 2009; Aryeetey, 2008; Asiama and Osei, 2007). However, predictors of loan default in the microfinance industry to our best knowledge have not received much attention.

Gender is recognized as one of the variables that affect credit risk in microfinance. Dyar *et al.* (2006) argue that women are considered to be ideal credit targets because of their proven propensity to meet their debt obligations compared to men. D'Espallier et al. (2009) investigate gender differences with respect to microcredit repayment performance using a global dataset covering 350 MFIs in 70 countries and show that MFIs with more women clients exhibit lower portfolio at risk, lower write offs, and lower credit loss provisions, all things being equal. Armendariz & Morduch (2005) report that Grameen Bank changed their focus from men to women due to repayment problems they faced with the former. Hossain (1988) reports that in Bangladesh 81 percent of women experienced no repayment problems compared to 74 percent of men. In their study, Khandker et al. (1995) find that 15.3 percent of Grameen's male borrowers had repayment problems compared to only 1. 3 percent of the women. The World Bank (2007) observes that repayment is higher among female borrowers, mostly due to more conservative investments and lower moral hazard risk. According to Emran et al. (2006), women are more likely to pay the high interest rates required by many MFIs because they are more restricted in their access to the formal labour market.

Notwithstanding the evidence in favor of women, there are few studies that find the gender factor an irrelevant factor in credit risk management. Bhatt & Tang (2002) find no significant relationship between gender and repayment. The study of Godquin (2004) in Bangladesh indicates that correlation between gender and repayment is positive but not significant. Adusei and Appiah (2011) conclude from their study in Ghana that female borrowers are not better than their male counterparts.

Apart from gender, there are other variables that have been found to influence default risk. Updegrave (1987) finds the following variables as significant determinants of consumer credit risk: the historic repayment record, bankruptcy history, work and resident duration, income, occupation, age and the state of savings account. Thus, Updegrave (1987) suggests that companies should include these variables in their credit risk analysis.

Steenackers and Goovaerts (1989) employ data on personal loans from Belgian Credit Company. The loans date from November 1984 till December 1986 and contain 995 good Loan, 1257 bad loans and 693 refused loans. Using logistic regression, they find the following results: age, resident and work duration, the number and duration of loans, district, occupation, phone ownership, working in the public sector or not, monthly income and housing ownership have a significant relationship with repayment behavior.

Bhatt and Tang (2002) study the determinants of loan repayment for four of the oldest microcredit programs in the US: the Neighborhood Entrepreneurship Program (NEP), Community Enterprise Program (CEP), First Chance (FC) and The Women's Development Association (WDA) using systematic data from the programs on six socio-economic variables deemed as important determinants of loan repayment in microcredit: (1) the borrower's gender, (2) the borrower's educational level,(3) the borrower's household income, (4) the degree of formality of the borrower's business, (5) the number of years that the borrower has been in business, and (6) the proximity of the borrower's business to the lending agency. They report that higher levels of education and proximity to the lending agency are found to increase the probability of loan repayment. They also find that low transaction costs for accessing loans and high borrower-costs in the event of default stimulate loan repayment performance. The study also finds that gender and homogeneity are not significantly related to loan repayment.

In Turkey, Özdemir and Boran (2004) explores the relationship between consumer credit clients' credit default risk and some demographic and financial variables with a logistic binary regression. Data employed for investigation are obtained from the customer records of a private bank in Turkey. Özdemir and Boran (2004) finds residential status as the only demographic variable that has a significant effect on default. The study also finds interest rate and maturity to have a positive, significant effect on the credit default risk. The study concludes that the longer the maturity or the higher the interest, the higher the risk for clients not paying their loans on time.

Vasanthi and Raja (2006) estimate the likelihood of default risk associated with income and other factors with data from Australia (Australian Bureau of Statistics, ABS 2001). In a sample of 3,431 households, the study finds that the age of the head of the household (the younger households tend to be negatively affected by the increasing burden of mortgage payments); income; the loan to value ratio; the educational level of the head of household and marital status are significance determinants of default risk. They conclude that the probability of default is higher with an uneducated, younger and divorced as head of the family compared to others.

Dinh and Kleimeier (2007) investigate the determinants of default risk with a database of one of the Vietnam's commercial banks. The study analyzes a sample of 56, 037 loans and finds that time with bank, gender, number of loans, and loan duration are important determinants of default risk. The study suggests that companies should update their credit scoring models (CSMs) regularly in response to economic changes.

Kočenda and Vojtek (2009) report from the Czech Republic that the most important characteristics of default behavior are the amount of resources the client has, the level of education, marital status, the purpose of the loan, and the number of years the client has had an account with the bank.

The length of the relationship between the loan client and the bank has been found to be the most important behavioral characteristic in default risk analysis. Evidence from the empirical literature (Hopper and Lewis, 1992; Thomas, Ho and Scherer, 2001; Anderson, 2007) shows that there is a positive correlation between the length of time the client has had an account with the bank and her or his ability to repay the debt. The explanation is that a bank knows clients with longer histories better than those with shorter histories, and therefore the bank can better foresee that the former group of clients will not default (Kočenda and Vojtek, 2009).

Horkko (2010) investigates the effect of socio-demographic and behavioral variables on default in Finland and finds that income, time since last moving, age, possession of credit card, education and nationality are the most significant socio-demographic variables that affect probability of default. The study also finds significant behavioral variables as the amount of scores the customer obtained, loan size and the information whether the customer had been granted a loan earlier from the same company.

On the basis of the literature, the following hypotheses are to be tested empirically:

H_1.Male loan clients are more likely to default on their credit than female clients

H_2. *The a*ge of a loan client is negatively correlated with probability of default

H_3. Educational level of a loan client should negatively and significantly correlate with probability of default

H_4. Loan size is positively related to probability of default

H_5. Interest rate is positively related to probability of default

H_6. *The m*aturity of a loan is positively related to probability of default

H_7. Loan cycle is negatively related to probability of default

3 Methodology

This section provides information on the methodology used for the study. It is in two parts: sample, sampling technique and data sources; and the model developed for the study.

3.1 Sample, Sampling Technique and Data Sources

754 loan clients of three MFIs Opportunity International Savings and Loans Company Limited and Bosomtwe Rural Bank) in Ghana are used for the study. The sampling technique is simple random sampling where data needed for analysis are randomly selected from databases of the three microfinance institutions.

3.2 The Model

In line with previous studies such as Kočenda and Vojtek (2009); Chen & Huang (2003), Thomas (2000), the study adopts binary regression model. Probability of default (PD) is the predicted variable. It is a dichotomous variable. It is set to 1 if the borrower defaulted and set to 0 otherwise. The independent variable is gender (GENDER). It is a dummy variable. It takes the value of 1 if the borrower is a male and set to 0 if the borrower is a female. The control variables are age (LnAGE), educational level (EDUC), loan size (LnLSIZE), interest rate (LnINT), maturity of the loan (LnMATURITY), and loan cycle (LCYCLE). Educational level is a dummy variable. Education takes the value of 1 if the borrower has tertiary education and 0 otherwise. The numeric variables are log-transformed to ensure standardization (Sarel, 1996).

The binary regression model is stated as:

$PD = \delta_1 + \delta_2 GENDER + \delta_3 LnAGE + \delta_4 EDUC + \delta_5 LnLSIZE + \delta_6 LnINT + \delta_7 LnMATURITY + \delta_8 LnLCYCLE + \eta_t$ *Where*

PD= Probability of Default. D=1if client is a defaulter; otherwise D=0
GENDER = Gender of loan client. D=1 if male; otherwise D=0
LnAGE= Natural logarithm of age of loan client
EDUC=Educational Level of Client. D=1 if male; otherwise D=0
LnLSIZE= Natural logarithm of amount of loan
LnINT=Natural logarithm of interest rate (1+r)
LnMATURITY=Natural logarithm of maturity of loan
LnLCYCLE= Natural logarithm of loan cycle (Number of times a client has borrowed from the microfinance institution
δ = is the parameter to be estimated
$\eta_t =$ stochastic error term

4 Main Results

The predictive power of the model measured by Cox and Snell and Nagelkerke R^2 lies between 38% and 51% which is reasonable. The descriptive statistics of the data are provided in Table 1. The average age of the clients is approximately 32. Approximately, GH¢ 4,821, 40%, 7 months and 4 times represent the means of loan size, interest rate, maturity, and loan cycle respectively.

Table 1: Descriptive Statistics on Continuous Data

Variable	Minimum	Maximum	Mean	Std. Deviation
Age	21	60	31.84	6.922
AMT	100	50,000	4821.21	6118.510
INT	30	41	39.56	1.759
DURATION	2	27	7.49	3.052
LCYCLE	1	13	4.19	2.229
N=754				

The descriptive statistics on categorical data (cross-tabulation of gender, client loan status, and education) are presented in Table 2. Of the 754 clients sampled, 484 representing 64.2% are females, whilst 270 representing 35.8% are males. It is obvious, that our data are skewed in favor of females. However, this is acceptable because microfinance usually seeks to empower women (Asiama and Osei, 2007).

Of the 484 females, 281 representing approximately 58.08% are non defaulters whilst 203 representing 41.92% are defaulters. Of the 270 males, 71 representing approximately 26.30% are non-defaulters whilst 199 representing 73.70% are defaulters. In all, 352 representing 46.68% are non-defaulters whilst 402 clients forming 53.32% of the sample are defaulters.

Out of the 754 clients, only 29 clients representing 3.8 have tertiary education. The rest have non-tertiary education. Of the 29, 20 forming approximately 69% are females whilst 9 representing 31% are males. It can be observed that the educational levels of the clients are low. Most of them have secondary, primary or no formal education at all.

Table 2: Cross-tabulation of Gender, Client loan Status and Education

GENDER	CLIENT LOAN STATUS			EDUCATION		
	Defaulters	**Non-defaulters**	**Total**	**Non-tertiary education**	**Tertiary education**	**Total**
FEMALES	281	203	484	464	20	484
MALES	71	199	270	261	9	270
Total	**352**	**402**	**754**	**725**	**29**	**754**

The results of the binary logistic regression are presented in Table 3. Gender variable has a significant, negative relationship with credit default, suggesting that compared to female clients, male loan clients are less likely to default on their microcredit than their female counterparts. Therefore, hypothesis H_1 is unsupported. This suggests to us that contrary to the position of the literature that females are better borrowers than males (D'Espallier et al., 2009; The World Bank, 2007; Armendariz & Morduch,2005; Khandker *et al.*, 1995; Hossain,1988), male borrowers in Ghana are less likely to default on their credit than their female counterparts. One explanation is that most female clients of microfinance tend to engage in small businesses such as food vending that do not generally generate much cash for prompt repayment of loans. Low level of education among women which is traceable to discriminatory cultural practices against women might have resulted in poor financial management leading to poor repayment performance. Another possible reason could be increasing financial obligations of women towards family which deplete their financial resources making them unable to meet their loan repayment obligations.

Age shows a negative, statistically significant relationship with default, suggesting that the older a loan client is, the less likelihood that he or will default. This is because older borrowers are more risk averse and will, therefore, be less likely to default (Dunn and Kim, 1999; Arminger *et al.* 1997; Agarwal *et al.* 2009). Hypothesis $H_{2,}$ thus, has empirical support. Age is a moderator of behavior. All things being equal, as a person grows older, the more careful he or she becomes and, thus, loans contracted are likely to be managed effectively to ensure their repayment.

Studies such as Harkko (2010), Kočenda and Vojtek (2009) and Vasanthi and Raja (2006) have found level of education as a significant predictor of default. The contention is that customers with a higher level of education have much less difficulty repaying their loans. Contrary to the position of the literature, our data do not provide support for this claim. As can be observed from Table 3, education has a positive, statistically insignificant relationship with probability of default. Hypothesis H_3 *is*, therefore, unsupported.

Evidence in Table 3 indicates that loan size has a positive, statistically significant relationship with default, indicating that the larger the size of a loan the higher the probability of default. This affirms hypothesis H_4. Microfinance clients are usually the poor and financially excluded in society. Therefore, when credit in large sizes is extended to them they are more likely to have difficulty repaying them. This explains the positive relationship between loan size and probability of default.

Özdemir (2004) reports that interest rate has a positive, statistically significant effect on the credit default risk. Contrary to this, our data provide evidence that interest rate has rather a negative, statistically significant relationship with probability of default. Hypothesis H_5 is, therefore, unsupported. The explanation may be that high lending rate wards off borrowers who do not have strong business opportunities. Besides, high interest rate may compel borrowers to utilize the funds with tact and circumspection so that they will be able to repay the loans to avoid embarrassment and harassment that usually characterize micro-credit default.

Özdemir and Boran (2004) find maturity of a loan to have a positive, statistically significant effect on credit default risk. The study argues that the longer the maturity of a loan, the higher the probability of default. This finding has been confirmed by our data. As can be observed from Table 3, maturity has a positive, statistically significant relationship with probability of default. Hypothesis H_6 is, therefore, validated.

The relationship between a loan client and the probability of default is one of the significant predictors of default in the literature (Kočenda and Vojtek, 2009; Dinh and Kleimeier (2007). Kočenda and Vojtek (2009) provide evidence to the effect that the longer the relationship between the customer and the lender, the more likely it is for the customer to pay back. Our data provide evidence that is consistent with this finding. Loan cycle (*Ln*LCYCLE) shows a strong negative, statistically significant relationship with probability of default, suggesting that repeat borrowers are less likely to default on their current loans than first-time borrowers. Hypothesis H_7 is, therefore, substantiated.

Table 3: Logistic Regression Results. Dependent Variable: Probability of Default

Variable	**B**	**Wald**	**p-value**
GENDER	-.624	10.001	.002***
*Ln*AGE	-6.169	34.210	.000***
EDUC	.593	1.845	.174
*Ln*SIZE	.768	7.757	.005***
*Ln*INT	-5.216	3.026	.082*
*Ln*MATURITY	1.159	3.485	.062*
*Ln*CYCLE	-.921	5.651	.017**
CONSTANT	7.233	13.502	.000***

***, **, * represent 1%, 5% and 10% significance levels respectively

5 Conclusion

The paper tests the validity of female superiority in loan repayment hypothesis in the microfinance industry with data purposively drawn from 754 loan customers of three MFIs (Opportunity International Savings and Loans Company Limited; Sinapi Aba Trust, and Bosomtwe Rural Bank). Logistic regression model which is touted to have more predictive power has been used for the study. The results of the analysis indicate that females are not better than males in loan repayment. Indeed, evidence shows that males are less likely to default on their loans than females. The results of the analysis also show that age, loan size, interest rate, loan maturity, and loan cycle are significant predictors of default. Level of educational is found to be an insignificant determinant of loan default.

To the extent that males have been found to have less probability of default, it is reasonable to suggest that lending more to creditworthy male clients could improve the repayment performance of MFIs in Ghana. However, this has social and economic costs in the midst of frantic efforts towards women emancipation. Lending more to creditworthy male clients means deepening the social and economic gap between males and females. Probably, finding the underpinnings of the poor repayment rate among women and developing the appropriate responses to them so as to extend more credit to women will be in line with the concept of microfinance.

The negative, statistically significant relationship between age and probability of default presupposes that MFIs must consider age as one of the critical factors in the micro-lending process. Lending more to older people who meet credit standards, all other things being equal, will boost the repayment performance of MFIs in Ghana.

To the extent that loan size positively and significantly correlates with probability of default, it is advisable for MFIs to critically consider the quantum of credit they extend to their clients. Thoroughly examining the purpose of the loan, the nature of client's business, the financial needs of a loan applicant, etc. could help in advancing optimal credit to each client.

Interest rate has been found to reduce probability of default. Over the years, policy makers as well as microfinance clients have bemoaned the exorbitant interest rates charged by MFIs. The contention is that high interest rates defeat the purpose of microfinance as a pro-poor financial intervention that holds the key to poverty alleviation. Our paper seems to offer some justification for high interest rates that usually characterize micro-lending: High interest rates promote probability of repayment. We do not attempt to argue that MFIs should be encouraged to charge skyrocketing rates on their loans insofar as their loan repayment performance will improve. Rather, we contend that clients whose risk profiles are high should be given commensurate interest rates as a way of flushing out speculative borrowers from the microfinance industry.

Evidence from the analysis suggests that the longer the loan period, the poorer its repayment. Therefore, it is proper for MFIs to take short-term positions in their micro-lending. Extending a loan-term loan aggravates the default risk of an MFI. Fortunately, most MFIs usually extend loans that have maturities of one year or less. It is only few MFIs that offer loans with maturities of more than one year.

To the extent that loan cycle has shown a negative, statistically significant correlation with probability of default, we submit that repeat borrowers in the microfinance industry have lower risk than first-time borrowers. It is, thus, reasonable to recommend that MFIs should factor this in the determination of their interest rates. Charging first-time borrowers and repeat borrowers the same interest rate is unfair to the latter because the latter's risk levels are lower.

In all, the current study contributes to the literature on the gender-repayment nexus by challenging the long-held position that females perform better than their male counterparts in loan repayment. Male borrowers are rather better borrowers. However, the actual reason for this remains one of the murky areas that require research attention in the future. We, therefore, recommend that future research should delve into the underlying reason(s) for better male loan repayment performance in Ghana.

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