Spring 5-23-2015

Gender Bias in Microlending: Do Opposites Attract?

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Abstract: In this study, we exploit a quasi-random assignment of clients to loan officers using a unique database and survey from a large microfinance bank in Nigeria to show that opposite-sex preferences affect credit demand and supply. We find that clients matched to loan officers of the opposite gender are more likely to receive credit and are more likely to return for an additional loan with the credit lender [1].

[1] I would like to thank my advisor, Professor Surpana Chakraborty for her consistent support, Professor Alessandra Cassar for her insightful feedback.

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1 Introduction

The institute of microfinance in 1972 and since then has been a strategy to provide credit to the poor and increase credit access in developing countries to people otherwise rejected by the formal financial institutions. Microfinance is targeted at end user clients such as business owners or local entrepreneurs. The growth of microfinance since then has expanded and theorized to improve economic welfare. Identity help form relationships, culture, and gender is an indicator of preferences *(Akerlof & Kranton, 2000)*. Similarity in gender serves to encourage group behavior dynamics. Gender grouping and identity causing trust, responsibility , and reciprocation based on shared norms and understandings *(Beck et al., 2011)*. This paper examines gender, a form of group identity, and the domino effect of gender matching for the credit market outcomes.

Microlending programs have been increasing to improve economic outcomes. Some notable examples of microfinance lending systems are Banco Sol in Bolivia and the Grameen Bank in Bangladesh, with the latter serving as a template for microfinance banks in developing countries today. Microfinance lending programs vary according to targets such as gender targeting or product targeting. Institutions like the Grameen Bank targets female clients while others offer lending programs aimed at reducing poverty levels by providing credit to clients otherwise denied by formal commercial institutions. It is however difficult to find out a general metric for client targeting by micro credit institutions because the ultimate approval of clients is determined by loan officers or field officers *(Brau & Woller, 2004)*.

The sex and credit hypothesis has gained the interest of researchers in recent years, as scholars try to understand factors that limit economic activities given credit channels. Credit outcomes based on treatment differences in loan conditions resulting from gender preferences. Recent research also suggest that there is a gender bias in institutional lending to borrowers *(Agier & Szarfarz, 2013; Beck et al., 2011)*. Debates surrounding the credit worthiness of female borrowers: groups or individuals *(D'Espalier et al., 2010)* buttressed by studies *(Armendariz & Morduch, 2005; Guerin & Mersland, 2005)* that loans targeted at women regardless of status yield positive welfare effects and repayments for the credit lender.

While these studies show the influence conscious gender bias and dissimilarities in repayments by gender on credit outcomes, studies on credit delivery channels are limited. A likely argument for this can stem from differences in lending mechanisms of credit lenders to applicants based on gender. However, no literature provides strong evidence for this phenomena. Indications that an established good faith of female credit worthiness is debunked by studies which show that female clients face increasing difficulty to credit access *(D'Espalier et al., 2010)*. This study aims to examine one channel of credit delivery influence, specifically loan officers or field officers, and investigate the direction of bias in microcredit.

Using data from a large microfinance institution in Nigeria, this study investigates the consequences of an opposite-gender match in credit receipt and if this influences the likelihood that the clients return for additional credit. Does gender preference affect loan decisions of field officers? What is the direction of bias in microcredit? This study aims to find if "opposites attract" or if "gender bonding" exists in microlending. Exploring social status, this study wishes to understand officer characteristics relative to gender identity. Issues stemming from bias in gender matching of clients matched to same or opposite-sex field officers are addressed through a quasi-random framework of first time client-officer relationships. This identification strategy allows for an analogous difference-in-differences estimation comparing outcomes for male and female clients assigned to male or female field officers. Baseline results include fixed effects controlling for all time-invariant effects across field officers, branches, sector, and time which may affect client-officer match. In addition, support for the interpretation is shown by the test statistics that the difference between clients prior to initial credit receipt is not significant between male and female officers.

The baseline estimates are consistent with accounts of unconscious gender preferences fueling loan conditions. The results suggest an association between opposite-sex matching of first time clients which impacts credit. First time clients matched with opposite-sex field officers are more likely to receive more credit and are likely to return to the lender for additional loans. On average, given loan approvals, male and female clients are more likely to receive more when matched to the opposite-sex loan officer. While the identification strategy does not allow reporting results as causality, there is evidence that support opposite-sex preferences.

The rest of the paper is organized as: Section 2 reviews the relevant literature; Section 3 provides background information about the microfinance lender and its lending system, outline of the method, and data description; Section 4 presents the results on the relationship between opposite-sex client-officer match on initial credit receipt and likelihood of applying for additional credit; Section 5 reviews and concludes.

2 Review of Relevant Literature

This section reviews the relevant literature and the contributions of this study to existing literature.

2.1 Background of Microfinance

Microfinance has become a popular phenomenon in recent years as opposed to previous lending societies comprising of commercial financial institutions. Before the influx of microfinance institutions, most societies formed social groups based on commonality. A social group made up of men and women from clothe weavers to hair stylists. In these group settings, members would gather once or twice a week to talk about the general issues regarding the group. Sometimes, these groups create a financial outlet to help its members who might want financial help. They also serve as a savings instrument for members to protect against economic shocks. Microfinance, which includes this system of lending, provides credit to groups and shares the burden of assuming financial stability for its members *(Armendariz & Morduch, 2005)*. Ensuring joint liability from group members for loan repayment, microfinance has opened up credit access to consumers requiring financial aid.

Although microfinance institutions give credit to both group and individual borrowers, there are benefits of engaging both types of lending in microfinance. Group loans can have a positive impact business activities *(Attanasio et al., 2011)* and discourage members from using credit for non-productive purposes. Individual borrowers are monitored and are not limited by joint liability of loan defaults as in group lending. Group lending improves accountability and reduces direct transaction costs to the microfinance *(Lanmond et al., 2007)*. Through group lending, lenders gain information about its clients such as errant clients and information that help to tailor microfinance programs. While lending models claim that group lending schemes are more successful than individual schemes, empirical studies have shown that most of this success is driven by underlining individual lending programs *(Rai, & Sjöström, 2000)*.

One of the hope for microfinance, besides serving clients otherwise excluded by the formal financial lenders, is that it will help to encourage the start of new businesses and adoption of new practices. With this goal, some microfinance institutions incorporate lending programs and target loans to specific end users. By providing credit to rural livelihoods *(Judith Shaw, 2004)* to reduce poverty by providing financial services to low-income households *(Morduch, 2005)*; to protect against health shocks *(Gertler et al., 2008)* by ensuring households are insured against loss in labor supply; microfinance programs provide a source of financial constant to customers. Similar to most simulations, the model of microfinance in Nigeria follows a similar trend by providing credit requiring little or no collateral and minimal interest rates. Providing credit as low as $70, with defined repayment terms, microfinance in Nigeria has helped provide an opportunity for clients who are underprivileged.

2.2 Best Practices in Microfinance

Literature on microfinance practices is extensive and includes aspects such as determination of optimal operational policies, effective lending mechanisms, and decisions on whether to lend to groups or individual clients. MFIs with the ultimate goal of profit maximization will decide interest rates to maximize shareholder wealth. However, charging rates too high will hinder other microfinance goals such as poverty reduction and could also increase number of loan defaults. Demanding higher interest rates to manage administrative and transaction costs and maintain financial self-sufficiency *(Brau, 2004)*. This results in a tradeoff between financial self-sufficiency and depth of program outreach.

The choice of every MFI to lend to individual or group clients is another best practice literature. Group lending reduces transaction costs, shows a positive correlation with reported entrepreneurship earnings, *(Woolcock, 2001; Gomez & Santor, 2001)* and make sure social collateral within groups. Individual lending improves monitoring, and it is easier for the borrower to secure recurring loans without the obstacle of joint liability found in group lending situations. This study adds to literature about the significance of best practices in lending mechanisms of microfinance. Through direct monitoring, regular repayment schedules, and the use of non-refinancing threats; MFIs like the one used in this study can infiltrate new areas of the credit markets and improve its popularity.

2.3 Microfinance Institutional Management

One of the goal a business has is to increase economic growth by increased revenue and business expansion, i.e. cut poverty. This leads an individual or a group to seek credit for investment or insurance against economic shocks *(Luotet et al., 2007)*. Most microcredit clients are female *(Agier & Szarfarz, 2013)* and loan conditions may vary across gender or target. Group clients ensure timely repayment through joint liability. By gaining capital gains via group meetings and self reporting, there are increases in recurring lending cycles *(Feigenberg et al., 2013)*. Group practices serve the opportunity of quicker loan repayments and access to higher credit lines. Field officers facilitate microfinance services *(Dixon et al., 2011)* by serving as the physical channel of credit distribution.

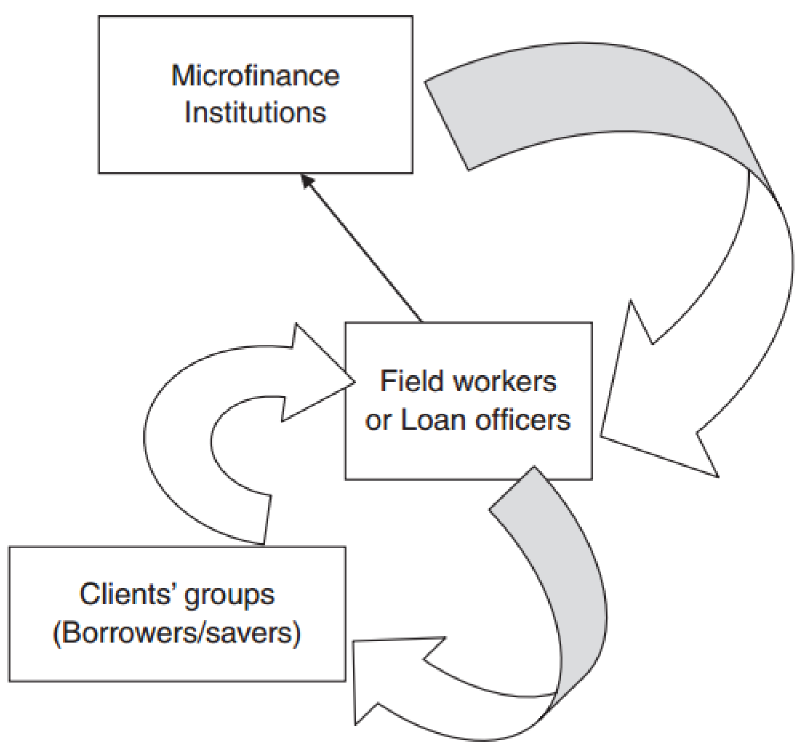

Figure 1: Relationship between Clients/Field Officers and Microfinance

The ultimate decision on credit applications is determined by the belief of the loan officer. While literature on this relationship between field officers and clients is limited, *(Siwale & Ritchie, 2011)* finds that field officers are critical to implementing of microfinance programs. Field officers inform clients about micro lending practices, maintaining loan portfolios, and providing support to clients as needed. Figure 1 depicts the relationship between clients and field officers in a microfinance. The clients have no direct relationship with the lender except through the field officers or loan officers. This could suggest that the likelihood an applicant will receive microfinance depends on loan conditions determined by the field officer.

2.4 Gender Targeting in Microfinance

Discrimination, in microfinance, is a situation where terms of a transaction is affected by personal preferences not related to existing law or business practices. Studies of preferences or discrimination in credit markets based on gender or on race explain a consensus that subtle behavioral preferences affect decision making. Differences in interest rates charged, loan approval rates, and other loan conditions of clients based on gender identity of the field officer affect loan outcomes of microfinance. Empirical studies suggest this disparity in credit availability is likely caused by discrimination *(Banchflower et al., 2003; Brau & Woller, 2004).*

Group identity, a predictor of social preferences, encourages favoritism which may lead to inefficient transactions and lost opportunities. Given the interaction between loan officers and clients in a microfinance institution, it is likely that gender preferences and social institutions will impact credit receipt and predict the likelihood of client returning for additional credit *(Beck et al., 2011)*. An alternative theory on the likelihood of additional credit and gender identity is that familiarity cuts or expands bias. Although some studies show that women are lower credit risks *(D'Espallier et al., 2011)* and should therefore experience higher credit availability, gender preferences often hinder credit to the female gender.

3 Data, Identification Strategy and Method

This section describes the data, provides information on the survey instruments used, identification strategy, summary statistics and method used for estimation.

3.1 Data

This study draws from two sets of data, both gotten from the First Bank Microfinance Institution in Nigeria. The first is a longitudinal panel containing the portfolio of loan transactions completed by the lender. The second dataset is drawn from the survey response obtained from field officers at the First Bank Nigeria (FBN) microfinance. The loan officer survey response data includes information about loan officer socio economic status such as education, experience, marital status and work environment statistics [2].

3.1.1 Database

The loan portfolio dataset includes nearly 4,000 loans transactions completed by the bank over the period of December 2009 to May 2014. The data contains information on 91 loan officers over the 22 branches of the bank [3]. The lender, FBN microfinance, is one of the earliest microfinance banks in Nigeria established in 2008 and regulated by the Central Bank of Nigeria. As one of the 720 MFIs in Nigeria and controlling less than 3% of the market, FBN microfinance provides microcredit to business owners and entrepreneurs *FBN Annual Report, 2013.* The lending policies adopted by FBN microfinance follow the group lending mechanisms of micro lending theories similar to *(de Aghion & Morduch, 2000)* [4] and the Grameen Bank.

[2]Some of the comments made on this study also stems from semi-structured interviews with the field/loan officers.

[3]The original dataset included close to 6000 observations across 23 branches. After data cleaning and accounting for missing observations, the dataset reduced to around 3,964 observations. The number of branches reduced to 22 because two branches within the same geographical location merged.

[4]The mechanisms believed to ensure success of MFI programs such as direct monitoring, regular repayment schedules, and the use of non-refinancing threats.

3.1.2 Survey Instrument

Loan officers employed by the MFI have the discretion on the approval of all loan applications, including assessment of risk, loan amount, collateral requests and other loan terms. The loan officer or field officer also has the responsibility of monitoring the repayment behavior of the borrower. Loans are disbursed to all successful applicants regardless of gender. The field officer manages the portfolio of both individual and group clients. Assignment of borrowers who visit the branches to officers is based on availability of the loan officers in the branch. First-time borrowers have a credit limit on initial applications regardless of the size of their business or social economic status. Loan cycles are 6-8 months. Each branch comprises of 4 to 5 loan officers and are supervised by a branch manager who reports to the region manager [5].

The survey data from a sample of 30 field officers used by the FBN microfinance is used to conduct the test on the influence of social economic preferences in credit receipts. The sample frame based on a representation of the population of field officers and a random draw [6]. A three-part survey instrument determined the loan officer decision making process. The first part asked questions on the field officer's current demographic status such as age, marital status and current branch station. The second part present the field officer with questions regarding education and work valuation scenarios. The third part collected information on the relationship with clients. The field officers were informed of the confidentiality of their responses and could respond to the best of their knowledge. The survey questions used for this study are included in the Appendix.

3.2 Identification Strategy

It is likely that loan officer characteristics might affect loan conditions as well as the decision to apriori choose a boorwer. To control for this probability, this study uses a quasi-random assignment of first-time clients to field officers and using a framework similar to difference-in-differences. This compares variations in outcomes for male and female clients

[5]The region manager stipulates the loan portfolio target for each branch and the branch manager ensures the achievement of the quota.

[6]Based on communication with the bank, available field officers were selected to be respondents

receiving credit from a male field officer to the variation for a male and female client receiving credit from a female field officer. It is possible that there are differences in field officer characteristics aside gender such as branch characteristics, potential similarities of borrowers and loan officers specializing in specific sectors, and time (month and year) which may influence borrower-loan officer match, the baseline report includes field officer, branch, sector, and time fixed effects.

Baseline regression coefficients control for fixed effects for field officers, branch, sector and time. Field officer effects help to control for unobserved characteristics aside gender. Branch effects help to control for variations in location absorbed by time or varying across branches. Sector fixed effects control for any sector bias that might be in the sample. Time fixed effects (month and year) control for changes in macroeconomic conditions. This study assumes that field officer lending practices over time such as monitoring and loan assessment is not statistically different across client gender. Following the specification used in Beck et al., 2011, I estimate the regression:

$$y_{ijmssb} = \beta cl_i fo_i + cl_i + fo_j + \sigma_m + \upsilon_y + \gamma_s + \tau_b + \epsilon_{ijmysb}$$

Where y_{ijmysb} is client i associated with field officer j in a particular month m and particular year y in sector s and in branch b; $cl_i fo$ is the client-officer dummy for client i and officer j being opposite gender. This dummy takes on the value 1 for each client matched to an opposite-sex loan officer and 0 otherwise. cl_i is the client dummy, fo_j is the field officer dummy, σ_m is the month dummy, υ_y is the year dummy, γ_s is the sector dummy, τ_b is the branch dummy. Under the assumption that $\text{Cov}(cl_i fo_j, u|z) = 0$, β shows if there is a difference between male and female clients if paired with a male or female loan officer. u is any other unobservable and z is a vector of fixed effects. The test statistics in this study checks for differences in borrower information (collateral), and field-officer information (age, experience, education). Standard errors are clustered at field officer level. The results of the t-tests are shown in the table 1.

Table 1 shows that there are no significant differences in the observed characteristics between the relationship of a client and field officer before loan acquisition. The table shows the tests across the subsamples (field officer variables) used in the analysis of the study. I believe this lends significance to examination the study is analyzing. The variable Amount Disbursed in table 1 is a sample t-test to test the overall difference in the total amount disbursed to clients as determined by a male officer or female field officer.

Table 1: Test for Differences in Field Officer Characteristics

Variable	Coefficient	Standard Error
Experience	0.038	(1.171)
Field Officer Age	0.048	(0.192)
Education	0.058	(0.040)
Christian	0.039	(0.023)
Married	0.028	(0.023)
Amount Disbursed	0.031	(0.025)

This table reports a test of difference in client and field officer characteristics. The coefficient reports the estimates from regressions of the respective variable on a dummy variable taking the value of 1 if a client is matched with an opposite sex field officer equation 1.The regressions are estimated conditioned on field officer, branch, sector, and time fixed effects. Standard errors are clustered at field officer level. ***, **, * show significance at 1, 5, and 10 percent level, respectively.

3.3 Sample Composition and Summary Statistics

This study aims to analyze the treatment differences on the following outcomes: (i) initial loan that a borrower receives, and (ii) the likelihood that the same borrower applies for a second loan with the MFI. While this study does not have information on rejected loan applications, almost all first time applicants receive loans from the bank [7]. While this study admits this lack of information is a significant limitation of the study, previous literature suggests low rejection rates make it difficult to detect bias *(Beck et al., 2011)* as there are high approval rates of loan applications. A simple t-test is used to show that the treatment difference in disbursed amount between male and female field officers is not statistically significant. For this study, I restrict the data in two ways. First, by restricting the data to initial loan cycles, I assume that first time borrowers have no prior relationship with the field officers and that subsequent loan cycles will indicate information on both loan officer and client or borrower. This information then helps in determining the changes in subsequent loan conditions. This initial

[7] From interviews conducted with field officers and borrowers.

regression would help present an easy test of a possible gender bias. Second, the data is restricted to loans disbursed to individuals. Loans to legal entities are dropped from the sample because there is no information on the gender of the client or borrower.

Summary statistics are presented in Table 2 and it shows that 51% of the clients are male, 48% of the sample are clients assigned to field officers of the opposite gender. Of the 48 % clients in an opposite-sex match, 23 % are male clients matched to a female field officer and 24 % are female clients assigned to a male field officers.35 % of the borrowers applied for a subsequent loan while 55% of the loan transactions distributed in urban areas. 46% of the loan officers are female, the average age around 32 years and the overall average field officer experience in the MFI is two and a half years. The survey instruments report that 12 % of the sample are Christians and 27 % have a higher degree. To test the interaction between client gender and loan officer outcomes, this study uses a framework similar to difference-in-differences estimation by comparing outcomes for male and female clients associated with a male officer to male to the difference of being assigned to a female loan officer.

Table 2: Summary Statistics

Variable	N	Mean	SD
Male Client	3967	0.509	0.499
Clients assigned to Opposite Sex Field Officer	3967	0.474	0.499
Male clients assigned to Female Field Officer(initial loan)	2583	0.230	0.421
Female clients assigned to Male Field Offices(initial loan)	2583	0.242	0.428
Likelihood of applying for a second loan	3967	0.348	0.476
Urban	3967	0.552	0.497
Credit Received (log of credit disbursed)	3967	12.334	0.799
Field Officer Covariates			
Female Field Officer	3967	0.464	0.498
Age Field Officer	498	32.309	3.415
Overall Field Officer Experience (months)	492	32.17	15.316
Christian	489	0.123	0.328
Education	492	0.27	0.680

This table reports summary statistics [observations, mean, and standard deviation].

3.4 Methodology

To examine the treatment differences in outcomes earlier specified, I use OLS to estimate the bias on initial credit received using the specification:

$$LoanDisbursed_{ijmysb} = \beta cl_i fo_i + cl_i + fo_j + \sigma_m + \upsilon_y + \gamma_s + \tau_b + X_{ijmysb} + \epsilon_{ijmysb}$$

where *LoanDisbursed* is the outcome of interest for client i associated with field officer j in a particular month m and particular year y in sector s and in branch b; $\beta cl_i fo_j$, estimates the impact of being assigned to an opposite sex loan officer on the outcome variable, disbursed amount. It measures the effect from a male (female) client matched with a female (male) field officer. The parameter $X_i jmysb$ contains a vector of client and loan officer characteristics. The above specification applies to three estimates to provide direction of officer gender responsible for the potential bias. The first estimation will report baseline estimates of treatment outcome for a first-time client assessing a loan if matched to an opposite gender field officer. The second estimation will report the effect on loan disbursement for a male client matched to a female field officer and the third estimation will report the effect on loan disbursement for a female client matched to a male field officer.

To examine the treatment difference on the second outcome, likelihood of applying for a second loan, I use a Probit model to estimate the specification similar to *(Greene, 2003; Imai et al., 2010)*:

$$D_i^* = aX_i + u_i$$

$$D_i^* = 1$$

$$if D_i^* = aX_i + u_i > 1$$

,

$$D_i^* = 0, otherwise$$

where: Pr $(D_i = 1|X_i) = \omega(a'X_i)$, Pr $(D_i = 0|X_i) = 1 - \omega(a'X_i)$, D_i equals 1 for every client who has over one loan cycle with the MFI and 0 otherwise. X_i is a vector of client and officer characteristics. ω is the standard normal cumulative distribution function.

4 Results

This section presents the findings of the estimation on the relationship between opposite-sex matching in a credit market. The results for initial credit received and the results on the likelihood of applying for additional credit with the lender.

4.1 Gender Match and Initial Credit

I first examine the effect of gender matching on the initial credit that a borrower receives from the field officer of opposite-sex as specified by the literature. Table 3 presents the results of estimating the impact of preference on amount received, along with fixed-effects. Column (1) presents differences without the loan officer characteristics while column (2) presents the treatment differences for client i assigned to opposite sex officer j including loan officer characteristics, client, loan officer, time, sector, and branch fixed effects.

Table 3: Gender Match and Initial Credit

	Initial Loan	
	(1)	(2)
Clients assigned to opposite-sex field officer	0.038	-0.096
	(0.04)	(0.10)
Loan Officer Characteristics	No	Yes
Location Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Sector Fixed Effects	Yes	Yes
Client Fixed Effects	Yes	Yes
Observations	2,853	251
Adjusted R-Squared	0.096	0.097

Outcome of interest: credit disbursed after restricting the data to first loan cycle. The regressions are conditioned on client, field officer, branch, sector fixed effects. The regression includes client and field officer covariates. Robust standard errors are clustered at Field Officer Level and are shown in parentheses. ***, **, * indicate 1, 5, and 10 percent level of significance respectively.

From Table 3, it is difficult to determine the association of group identity in credit outcomes. Without controlling for loan officer characteristics, there is a positive association between credit outcomes and being matched with a field officer of the opposite gender. However, by controlling for field officer covariates, the association is switched and it is likely that this leads to a negative bias. While these results are not statistically significant, these two tables lend to literature that finds a positive or negative preference of group identity on credit outcomes.

Table 4: Gender Matching and initial Credit

	Loan Cycle=1		
	(1)	(2)	(3)
Male Client/Male Loan Officer	0.086	1.132	2.611
	(0.071)	(0.406)	(2.168)
Female Client/Male Loan Officer	0.057**	1.013***	2.048
	(0.025)	(0.036)	(0.920)
Male Client/Female Loan Officer	0.181***	0.199***	1.053***
	(0.047)	(0.045)	(0.022)
Loan Officer Characteristics	No	Yes	No
Location Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes
Loan Officer Fixed Effects	No	No	Yes
Adjusted R-Squared	0.197	0.159	0.216
Number of Observations	2,583	251	2,583

All standard errors in parenthesis are robust and clustered at the loan officer level. Output of opposite-sex match and initial credit. All outputs include time, sector, location, client fixed effects. ***, **, * indicate 1, 5, and 10 percent level of significance respectively.

Specifying a more complete model, this study examines the effect of gender matching on the initial credit that a borrower receives from the field officer decomposed by gender matches. Table 4 presents the results decomposed by gender match. Column (1) presents the treatment differences for client-officer match excluding any information on Field Officer characteristics or fixed effects and including client, time, sector, and branch fixed effects. In column (2), client and loan officer characteristics are included but loan officer fixed effects are excluded. Column (3) presents the effect on loan differences with loan officer fixed effects but no loan officer characteristics. All specifications are robust and clustered at the field officer level.

The coefficients in columns (1) - (3) support the direction of potential bias is positive across all the specifications. Given initial loan cycle, there is a positive association between being specifically matched to a field officer of the opposite gender. Male and female clients in an opposite-sex match are more likely to receive more loan amount statistically significant at 1% level. One might assume that any of the characteristics (such as experience, education, age, marital status) also play an impact in the initial credit clients receive from a microfinance. This is distinct to studies such as *Beck et. al (2011)* that report a negative association of an opposite sex match in credit outcomes.

4.2 Gender Match and the Likelihood of Applying for Additional Credit

The second estimation examines the effect of opposite-sex identity on the likelihood that clients apply for subsequent credit with the lender. Table 5 presents the results from probit specification with the dependent variable a dummy taking 1 if the client applied for a second loan.

Column (1) - column (3) present the estimate with location, month, year, sector, and client fixed effects. Column (2) controls for loan officer characteristics while column (3) controls for field officer fixed effects. The results show that given female client and male officer initial loan match, a female borrower is more likely to returning to the loan officer and microfinance for a second loan. However, we do not find this a similar pattern of a male client matched to a field officer of the opposite sex. It is possible that female clients feel more confident about approaching the microfinance for more loans or women are better credit risks than male clients *D'espallier et al., (2010)*. Significant at 5% level, a female client is 18.1% more likely to return to the loan officer for a second loan.

Table 5: Likelihood of applying for a second loan

	Probability of Applying for Additional Loans		
	(1)	(2)	(3)
Male Client/Male Loan Officer	0.039	−0.292	−0.346
	(0.032)	(0.444)	(0.454)
Female Client/Male Loan Officer	0.033**	0.181**	0.244***
	(0.017)	(0.089)	(0.082)
Male Client/Female Loan Officer	0.013	0.156	0.196
	(0.024)	(0.943)	(0.996)
Loan Officer Characteristics	No	Yes	No
Location Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes
Loan Officer Fixed Effects	No	No	Yes
Adjusted R-Squared	0.087	0.125	0.165
Number of Observations	3,965	424	3,965

Output shows marginal effects on the likelihood of a client returning to officer for a subsequent loan. Standard errors in parenthesis are robust and clustered at the loan officer level. Outputs include time, sector, location, client fixed effects. ***, **, * indicate 1, 5, and 10 percent level of significance respectively.

Robustness Check

As a robustness check, this study examines another specification to test the impact of group identity on subsequent loans. We test the hypothesis that given the familiarity developed between the loan officer and the client from the initial loan conditions, if the bias is still existent.

Table 6 reports the estimates on the impact of a decomposed gender match on loan outcomes. This study finds that after the initial loan is completed, bias is eliminated and female clients matched with male loan officers seem to receive less in loan amounts in subsequent loan cycles significant at 5% and 1% level. It is likely that familiarity has impacted credit outcomes

Table 6: Gender Match and Subsequent Loans

	Gender and Subsequent Loans		
	(1)	(2)	(3)
Male Client/Male Loan Officer	-0.002	-0.858	-1.2719
	(0.071)	(1.773)	(1.328)
Female Client/Male Loan Officer	-0.109	-0.928^{**}	-1.792^{***}
	(0.077)	(0.495)	(0.002)
Male Client/Female Loan Officer	0.029	0.820	0.925
	(0.082)	(0.916)	(1.956)
Loan Officer Characteristics	No	Yes	No
Location Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes
Loan Officer Fixed Effects	No	No	Yes
Adjusted R-Squared	0.224	0.131	0.265
Number of Observations	1,384	176	1,384

All standard errors in parenthesis are robust and clustered at the loan officer level. Output shows the treatment difference after initial loan cycle. All outputs include time, sector, location, client fixed effects. ***, **, * indicate 1, 5, and 10 percent level of significance respectively.

and the behavior of loan officers is affecting credit outcomes.

5 Discussion and Conclusion

This paper sets out to provide direction of gender preferences and how these preferences influence outcomes in the credit market. Using dataset from FBN microfinance, first-time clients assigned to opposite-sex field officers are more likely to receive credit than when matched with the same gender field officer. These results however show ambiguity about the specific socio-economic factors that underline the detected preference in the behavior of field officers. While these findings find no significant effect of the likelihood that clients return to the lender for subsequent loans, it is likely that given an opposite-gender match, clients are likely to return for subsequent loans. Specifically, this study finds that a female matched to a male field officer on the initial loan is more likely to return to the field officer for additional credit. It is possible that the participants will have enough information about each other which will help determine the conditions of subsequent loan transactions.

This study has shown that group identity, by gender preferences is evident in developing countries even with an evenly split sample. More importantly, it finds that bias found in initial credit outcomes does not exist in subsequent loans and that female clients in an opposite-sex match receive less from the loan officers. It is however possible that this preference will be less clear in a developed country setting. This paper adds to literature on gender matching in microcredit specifically in a developing country context. From a policy perspective, the findings in this paper point to the possibility that part of the impact of microfinance stems from the preferences of the loan officers and that the credit market can be improved by targeting policies to reduce preferences such as incentives and reward systems.

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Appendix

Survey Instrument

1. What Branch of First Bank do you currently work at?
2. What is your Last Name?
3. What is your Client Officer ID?
4. Gender
5. Religion
6. Age
7. Marital Status
8. Do you have any children?
9. Are you the head of the household?
10. Where do you live?
11. What is your Highest Educational Qualification?
12. Do you have any Professional Qualification?
13. If yes to the above, what is the name of the qualification?
14. How long have you been a Client Officer at FBN Microfinance (in year & month)
15. How long have you been working at this branch?
16. Since you have been a Client Officer, have you transferred to another branch?
17. In the past 6 months, have you transferred to another branch?
18. How would you describe the working environment at FBN Microfinance?
19. Are you allowed to choose your clients?
20. Is there a quota system of clients?
21. How often do you take up new clients?
22. How many clients do you manage?
23. What type of clients do you manage? (individual or group)
24. Do you deny loan applications? How often do you deny applications?
25. Do you have a personal relationship with your clients?