To Profit or not to Profit? A multilevel analysis of Microfinance institutions' financial outcomes

RODRIGO DE OLIVEIRA LEITE
Escola Brasileira de Administração Pública e de Empresas - FGV
LUIZ CLAUDIO FERREIRA SACRAMENTO JUNIOR
Escola Brasileira de Administração Pública e de Empresas - FGV
LAYLA DOS SANTOS MENDES
Escola Brasileira de Administração Pública e de Empresas - FGV

Abstract

We used a multilevel approach on comparing for-profit and not-for-profit microfinance institutions (MFIs). The database was comprised of 198 MFIs (52 countries), from the most widely used microfinance dataset (the MIX market), with a total of 661 observations from 2010 to 2014. Four financial accounting outcomes were considered: yield on gross portfolio (Yield), return on assets (ROA), portfolio at risk: 30 days (PAR30) and operational self-sufficiency (OSS). While for-profit MFIs had a higher yield, there was no significant effect of profit-orientation on ROA, PAR30 and OSS. Further analysis using propensity score matching showed that, while profit orientation has a significant effect in the yield on the small MFIs, it does not have an effect on larger MFIs, what is consistent with the theory that larger MFIs can distribute better its fixed costs, requiring lower interest rates and allowing smaller yield on gross portfolio. We also show that the intrinsic characteristics of the MFIs account for the majority of the four outcomes variance (70%), with time accounting for 25% and region characteristics accounting for only 5%.

Keywords: Microfinance, Financial Efficiency, Poverty Policies, Financial Accounting Indexes.

1. Introduction

In the last decades, microfinance has been achieving more and more prominence in the policy-making for the poor people (Morduch, 1999). Muhammad Yunus, the pioneer of microfinance, founded the Grameen Bank in 1976, and for that received the Nobel Peace Prize thirty years later. However, there is no much agreement in how should microfinance institutions (henceforth MFIs) be structured in order to achieve the best results in alleviating poverty.

There are advocates for both approaches of for-profit and not-for-profit MFIs. Morduch (2000) expressed those different points of view. Those that advocate for the profit-oriented approach of microfinance claim that with profits an MFI can achieve self-sustainability and expand their loan portfolio to help more people. They also claim that not-for-profit MFIs are less efficient and cannot survive without subsides. As Norell (2001) notes, a not-for-profit MFI can signal to their clients that the key concern is their well-being and not the financial return, what can lead to the opportunistic behavior of strategic default. However, those that advocates for the not-for-profit approach express their concerns that for-profit MFIs may explore the poor with higher interest rates and become the "new moneylenders". They also claim that, as long as poverty exists, there will be subsides for MFIs, since reducing poverty is a key element in the policy-making of all governments.

There are examples of MFIs that were founded as not-for-profit, and then became for-profit enterprises. Schmidt (2013) cites two very well known cases: Compartarmos in Mexico and SKS in India.

Compartamos was founded in 1990 as an NGO, but in 2007 it released its IPO. However, they did not create new shares in the IPO process, therefore they did not receive new funds. Several authors (Ashta & Hudon, 2012; Rosenberg et al., 2009; Schmidt, 2013) have criticized the IPO and the interest rates charged by Compartamos. The incentives alignment is controversial since the goal of open companies is to maximize the shareholders' return, but MFIs clients are mostly poor from developing countries.

However, although there is credit elasticity for poor clients (Karlan & Zinman, 2008), there is evidence that the loans made by Compartamos, even with high interest rates, do achieve some positive outcomes (Angelucci et al., 2015). It was found that those loans had a modest positive impact in business size, trust, and female decision making, and a modest negative impact in depression and reliance on or need for aid.

The SKS MFI was founded in India in 1998 and released its IPO in 2010. SKS adopted, as Compartamos, the policy of high interest rates. This policy is credited for the crash of microfinance in India in 2010 (Wichterich, 2012).

During the crises the SKS shares price dropped 77%. The crises was originated in Andhra Pradesh, and even is suspected to cause a number of suicides (CGAP, 2010), resulted in the "indebtedness of 82 percent of rural household" (Wichterich, 2012), and over 35,000 people lost their jobs in Andhra Pradesh.

Therefore it seems that exists anecdotal evidence for "the good and the bad" side of for-profit high-interest MFIs. Zeller & Meyer (2002) argued for the "triangle of microfinance" that is: financial sustainability, outreach, and impact. Those three "legs" would only be achieved if the MFI had profits, in order to be self-sustainable and growth (achieving more people, and giving larger loans).

However, profit-oriented MFIs tend to have different goals than not-for-profit ones. Cull et al. (2007) shows that profit-oriented MFIs tends to lend to the "richest of the poor", in order to achieve a higher level of profitability.

Armendáriz & Morduch (2010) list five often used financial accounting ratios that are important for a MFI to be sustainable: Financial Self Sufficiency (FSS), Return on Assets (ROA), Portfolio at Risk after 30 days (PAR30) and Yield on Gross Loan Portfolio (Yield). Nevertheless, Cull et al. (2011) shows that the FSS ratio may be biased, since grants, donations, and other alternative ways of funding are not included in the FSS calculation, making not-for-profit institutions score lower in this financial ratio, although the funding for those institutions being stable over years (Morduch, 2000).

Using a database of 198 MFIs (52 countries), with 661 observations, from 2010 to 2014 in a multilevel model, we expect to contribute to the discussion of those two different approaches and their impact on several different outcomes.

2. Methodology

2.1 Sample

We used a database provided by the Microfinance Information eXchange, Inc. (MIX). The data is self-reported, what can create a problem if a MFI reports untruthful figures. However, MIX did an audit in a number of MFIs in 2013-2014 period, and we used only MFIs that were audited. Also only observations that contained non-missing data for key variables were used. Table 1 shows the sample distribution by reach one of the six regions.

Table 1: Sample for this study

Region	**# MFIs**	**# Obs.**
Africa and Middle East	18	46
East Asia and the Pacific	20	60
Eastern Europe and Central Asia	38	146
Latin America and The Caribbean	80	280
South Asia	42	129
Total	**198**	**661**

2.2 Measures

All the four financial accounting measures (ratios) used as dependent variables were taken from Armendáriz & Morduch (2010) as follows: Yield on Gross Loan Portfolio, Return on Assets, Portfolio at Risk after 30 days, and Operational Self Sufficiency.

The first measure is Yield on Gross Loan Portfolio, which is fundamental for this study. This variable is measured using the interest and fees on loan portfolio divided by the average gross loan portfolio for that period. In addition, the variable is in real economic terms, considering inflation. It measures how much the MFI is actually receiving in interest and other payments from its clients. This is another way to measure how much the MFI is charging their clients.

The second measure, Return on Assets is represented by the net income (after taxes, grants and donations) divided by the average of assets. It measures how well the institution uses its assets to generate net income.

The third common measure applied here is the Portfolio at Risk for the period of 30 days, when the client is considered entering into arrears. This metric explains portion of the loan portfolio affected by delinquency as a percentage of the total portfolio. Although in traditional lending the delinquency is usually measured after a client is 6 months into arrears, in microfinance, due to the fact that there is not a collateral in most lends, a more conservative estimation is used. In addition, Norell (2001) cites that the industry's standard is 5% of PAR30.

Finally, OSS presents the received revenue over the cost of raising capital. This measure uses sources of costs as financial expense, provision for loan-loss and operational expense in the denominator. Hence, it shows if the MFI is able to afford its costs and perpetuate its operations. A value of 100% (considering that we multiplied our variables by 100) means that the bank can afford their costs. Values higher than 100% are desirable, since they can offer a financial slack for the MFI to undertake new projects. Nevertheless, a very high value may be an indicator that the MFI is exploiting their clients.

Our interest independent variable is Profit, which received the value of 1 if the MFI was registered as profit-oriented and 0 otherwise (not-for-profit). This variable will be interpreted as the difference in the dependent variable for the MFIs that are seeking to profit and those that do not. We used a number of control variables: size (small, medium, large), age (new, young, mature), clients (percentage of female borrowers and retention rate of borrowers) and staff turnover rate. We used the categories small (outreach less than 10,000 clients) and new (1 to 4 years) as baseline in the regressions that are presented in Table 4.

In order to represent the results in a more meaningful way, we chose to multiply our variables by 100, to make our interpretation more straightforward. With these four financial accounting ratios we are able to compare the performance of profit and non-profit MFIs controlling for the variance between the levels.

2.3 Method

We used a multilevel approach with a three-level hierarchical model, as specified in the null model. Equation (1) shows the specification of the first level. The dependent variable (Y_{ijk}) of the year i, MFI j, and Region k is a function of the mean of the dependent variable of MFI j and Region K (β_{0jk}) plus a random error ($\varepsilon_{\mathrm{ijk}}$) representing the variance across time, normally distributed with mean zero and variance of σ_{ε}^{2} ($\varepsilon_{\mathrm{ijk}} \sim N(0,\sigma_{\varepsilon}^{2})$).

Level 1 (Time): $Y_{ijk} = \beta_{0jk} + \varepsilon_{\mathrm{ijk}}$

(1)

Equation (2) shows the second level of analysis, where the mean of dependent variables across time of MFI j of the Region k (β_{0jk}) is a function of a mean dependent variables of Region k (γ_{00k}) plus a random error ($r_{\mathrm{0jk}} \sim N(0,\sigma_{r}^{2})$) representing the variance between MFIs.

Level 2 (MFI): $\beta_{0jk} = \gamma_{\mathrm{00k}} + r_{\mathrm{0jk}}$

(2)

Finally, equation (3) formalizes the third level analysis, where the mean dependent variables of the MFI j in Region k (γ_{00k}) is a random variable that is a function of the grand mean of the sample (δ_{000}) plus the random errors of the third level ($\mu_{00k} \sim N(0,\sigma_{\mu}^{2})$).

Level 3 (Region): $\gamma_{\mathrm{00k}} = \delta_{000} + \mu_{00k}$

(3)

Equations (4) depict the multilevel model with our IV (P_{ij}) and the random intercepts at the MFI and at the region levels.

Level 1 (Time): $Y_{ijk} = \beta_{0jk} + \beta_{1ij}P_{ij} + \varepsilon_{\mathrm{ijk}}$

Level 2 (MFI): $\beta_{0jk} = \gamma_{\mathrm{00k}} + r_{\mathrm{0jk}}$

(4)

Level 3 (Region): $\gamma_{\mathrm{00k}} = \delta_{000} + \mu_{00k}$

Equations (5) depict the multilevel model with our IV (P_{ij}), the controls (C_{nij}) and the random intercepts at the MFI and at the region levels.

Level 1 (Time): $Y_{ijk} = \beta_{0jk} + \beta_{1ij}P_{ij} + \sum_{n=1}^{7} \beta_{(n+1)ij}C_{nij} + \varepsilon_{\mathrm{ijk}}$

Level 2 (MFI): $\beta_{0jk} = \gamma_{\mathrm{00k}} + r_{\mathrm{0jk}}$

(5)

Level 3 (Region): $\gamma_{00k} = \delta_{000} + \mu_{00k}$

We chose to use the hierarchical model because it allow us to verify the heterogeneity of the firms across several levels. The research problem requires us to use controls in the estimation, since we know that hierarchical structure cannot sustain the assumption of independence (Raudenbush & Bryk, 2002). For instance, since MFIs are in the same region they are susceptible to similar elements, as we will see in the size of ICCs (Intra-Class Correlations) for region. Moreover, this technique allows identify how much of variance can be explained by each one of the three hierarchical levels as we will see in the next section. Also, since all the variables are endogenous, the multilevel model with random intercepts allows each MFI and each region to have its own intercept what controls for endogeneity at the MFI and region levels, as Hanchane & Mostafa (2012) noted.

3. Results

The results can be observed in Table 2. The null model describes the dependent variables variance discriminated by the three levels (Region, MFI and Time). Those models are presented in the columns 1, 4, 7 and 10. For the Model 1 we see that the time level explains 8.33% of the variance of Yield, 77.91% is explained by MFI level and 13.76% by region level. For the model 4 the results with ROA as dependent variable are, time explains 26.51% of variance, 73.49% is explained by MFI level and the region level does not explain any meaningful amount of the overall variance. The values for the MFI level are quite similar to the Model 1 which indicates that ROA and Yield variables variances are driven mainly from factors at the MFI level. For the PAR30 time becomes more relevant, since it accounts for 39.91% of variance. The MFI level loses weight going to 56.31% and Region explains 3.78%. Finally, the OSS variance is 74.70% in the MFI level. Time explains 24.19% of variance and region only 1.12%.

The more distinctive results is the highest variance explanation for Yield (13.76%) at Region level. Moreover, the MFI level at PAR30 has the lowest variance when compared to the other three indexes (ranging from 73.40% to 77.10%). Time have the highest variance explanation for PAR30, and lowest for Yield. The MFI level explains the most part of variance explained for all the dependent variables which implies that a hierarchical model can be useful see the variability of each MFI. Figure 1 shows it intuitively. This is consistent to our goal in order to observe the difference between profit and non-profit driven MFIs. The region, besides the lower variance, allow us to control for the heterogeneity in the data that can lead to biased estimation results.

The results indicate that in all models the profit dummy variable was not significant, except in Model 2 and Model 3. Interesting to note is that in Model 2 the coefficient is 7 significant at 1% level, though after including the controls it remained significant at 5% (Model 3). When we included the control variables the number of observations decrease due to missing data. We can infer no difference between profit and non-profit oriented MFIs for three out of four most common financial accounting measures used to compare the performance of microfinance institutions (Armendáriz & Morduch, 2010). Hence, the fact of profit maximizing behavior of firms are not contradictory of the main goal of microfinance.

In order to investigate further the difference between the profit and non-profit MFIs in the Yield ratio we subsampled according to firm size. We were motivated to do this analysis because this ratio was the only one that had a significant difference. Thus, we wanted to explore and find the mechanism that may explain this difference between for-profit and not-for-profit MFIs.

It is natural to expect that small MFIs require more profits (comparative to larger MFIs) to sustain their activity in order to be self-sustainable and grow its business, given its revenues are smaller. Moreover, larger MFIs have economies of scale due to fixed costs that can be dissipated in a larger portfolio (Gonzalez, 2007), so they may charge smaller interest rates (therefore reducing its yield on gross portfolio). The results for these estimations are presented in Table 3. The robustness of our findings was scrutinized with a 1-to-1 nearest neighbor propensity score matching with replacement. It was performed in order to make small MFIs comparable to large MFIs in the all observable variables but the profit dummy variable. The bias reduction achieved by this approach is shown at Table 4 and Figure 3.

The results occurred as theorized. The difference in average yield ratio, that can be interpreted as interest rates charged, it is prominent in smaller MFIs. This result is interpreted as follows: smaller profit-oriented MFIs need higher yield on gross portfolio (therefore higher interest rates) to maintain its growth and expand their portfolio (i.e., making more loans). However, there is no difference between profit-oriented and not-for-profit MFIs in the larger subgroup (right half of Table 3).

What drives this effect? We theorize that smaller not-for-profit MFIs can rely on alternative sources of financing (such as grants and donations) while for-profit MFIs need to “self-finance” themselves by increasing its revenues, since their fixed costs can only be distributed to a small number of clients. The larger profit-oriented MFIs can distribute their fixed costs in a larger portfolio, what enables them to charge smaller interest rates in comparison to the smaller ones (Gonzalez, 2007).

In addition, the ICC from firms at the MFI level is high at the models from Table 3. It suggests that a large percentage of variance of Yield on Gross Portfolio is at the MFI level. Further research must be done, but is relevant to hypothesize that the best approach for the MFIs is to be not-for-profit when smaller and after growth to change its nature to profit-oriented. This approach would allow smaller yields in all sizes: large and small. Unfortunately, few MFIs changed its profit status during time, what makes difficult to estimate its effects with a statistical approach.

4. Conclusion and Final Remarks

Our results show that not-for-profit MFIs can have as good financial accounting ratios (ROA, PAR30 and OSS) as for-profit MFIs, and also maintain lower interest rates for their clients. However, as Cull et al. (2011) notes, this does not mean that not-for-profit MFIs have as good outreach as for-profit MFIs, since for-profit MFIs may have better sources of financing itself in the market.

These results corroborate with other researches that show that there is not an intrinsically better microfinance approach between profit-oriented and not-for-profit institutions (Morduch, 2000; Schmidt, 2013). Each one serves a different purpose. While for-profit MFI's aims at the "richest-of-the-poor" (Cull et al., 2007), and have higher outreach, while charging larger interest rates (Cull et al., 2011), not-for-profit MFIs, although with smaller outreach, tend to serve the more poor, with lower interest rates.

However, we found that small profit-oriented MFIs have a larger yield on gross portfolio when compared to the not-for-profit ones. We theorize that it is due to the fact that not-for-profit MFIs have alternative sources of financing their activities, but the for-profit MFIs need a higher yield on gross portfolio to maintain self-growth. The large profit-oriented MFIs do not have a significant different yield when compared to the not-for-profit ones, what shows that larger MFIs are more efficient in their expenses, and also that they can distribute its fixed costs to a larger portfolio, enabling smaller interest rates.

Additionally, this study was able to estimate the importance of time, institutional characteristics and region on the four sustainability indexes used in the literature. On average, the intrinsic characteristics of the MFI accounts for 70% of the variance, while time accounted for 25% of overall variance. The effects of different regions are shown to be quite small, accounting for only 5% of overall variance. This shows that the intrinsic characteristics of firms have the biggest explanatory power and region characteristics explain a small portion of the financial indexes. This is an interesting finding since this shows that MFIs in different regions, but with equal intrinsic characteristics are quite comparable. This result gives robustness to experiments that are conducted across different regions such as Banerjee et al. (2015), Banerjee , Karlan and Zinman (2015) and Cull et al. (2009).

Despite the lack of exogenous variation, we try to diminish endogeneity effect by adopting three different methodologies. One is the traditional control variables approach (age, size, percentage of female borrowers, retention rate of borrowers and staff turnover rate). The second approach used was a multilevel model allowing for random intercepts, in which we break the variance and the error term. This multilevel approach can lead to more truthful and less biased conclusions (Hanchane & Mostafa, 2012). The third way was use a propensity score match to weight the regression with the probability of being smaller or a larger MFI.

Another issue is that the data entries are self-reported, which can result in misleading information given by the MFIs. We address this issue by using only data from audited MFIs. However, the only way to arrive at results that we can claim strict causality is by using either an experiment, a quasi-random setup (exogenous shock) or an instrumental variable approach. Nevertheless, none of these approaches are feasible in this study, especially the experimental approach, since we cannot randomly assign the MFI's to be for-profit or not-for-profit.

A second limitation is that many MFIs did not report all the information that were used as controls variables, what reduced our sample, and consequently diminished our statistical power. However, even with a smaller statistical power, we were able to achieve statistical significant effects.

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6. Appendix

Table 2: Results from hierarchical estimations

	Yield on Gross Portfolio			Return on Assets		
	M1	M2	M3	M4	M5	M6
Profit (1 = yes)		5.851**	4.627*		0.527	0.267
		(2.093)	(2.058)		(0.836)	(0.988)
Constant	24.035***	21.660***	10.760	2.317***	2.092***	0.863
	(2.928)	(3.253)	(5.853)	(0.411)	(0.543)	(2.586)
Variance Components						
Region level	35.986	42.568	74.803	0.000	0.033	0.392
	[13.76%]	[16.43%]	[31.65%]	**[0.00%]**	[0.08%]	[0.94%]
MFI level	203.748	194.799	141.102	29.563	29.455	29.441
	[77.91%]	[75.16%]	[59.70%]	**[73.40%]**	[73.27%]	[70.96%]
Time level	21.792	21.795	20.439	10.714	10.715	11.657
	[8.33%]	[8.41%]	[8.65%]	**[26.60%]**	[26.65%]	[28.10%]
Total variance	261.526	259.162	236.344	40.277	40.203	41.489
Observations	660	660	443	661	661	444
Mean Dep. Var.	23.713	23.713	23.713	2.512	2.512	2.512
Control Variables	No	No	Yes	No	No	Yes
	Portfolio at Risk (30 days)			Operational Self-sufficiency		
	M7	M8	M9	M10	M11	M12
Profit (1 = yes)		0.366	-0.077		5.025	4.212
		(0.511)	(0.545)		(3.437)	(3.693)
Constant	3.393***	3.238***	6.844***	116.6***	114.5***	104.2***
	(0.454)	(0.507)	(1.602)	(2.159)	(2.531)	(9.393)
Variance Components						
Region level	0.647	0.675	0.000	7.515	6.402	0.000
	[3.78%]	[3.95%]	[0.00%]	**[1.12%]**	[0.96%]	[0.00%]
MFI level	9.632	9.603	7.995	503.230	498.471	423.703
	[56.31%]	[56.15%]	[59.46%]	**[74.70%]**	[74.65%]	[73.41%]
Time level	6.827	6.825	5.450	162.945	162.873	153.467
	[39.91%]	[39.90%]	[40.54%]	**[24.18%]**	[24.39%]	[26.59%]
Total variance	17.106	17.103	13.446	673.689	667.747	577.170

Observations	643	643	433	661	661	444
Mean Dep. Var.	3.450	3.450	3.450	117.025	117.025	117.025
Control Variables	No	No	Yes	No	No	Yes

Std. Errors in parenthesis. Percentage of Variance explained in brackets. As control variables we used size (small, medium and large), age (new, young and mature), % of female borrowers, borrower retention rate and staff turnover rate. The categories small and new are baseline. ***p<.05 **p<.01 ***p<.001

Figure 2: Percentage of variance explained by each level

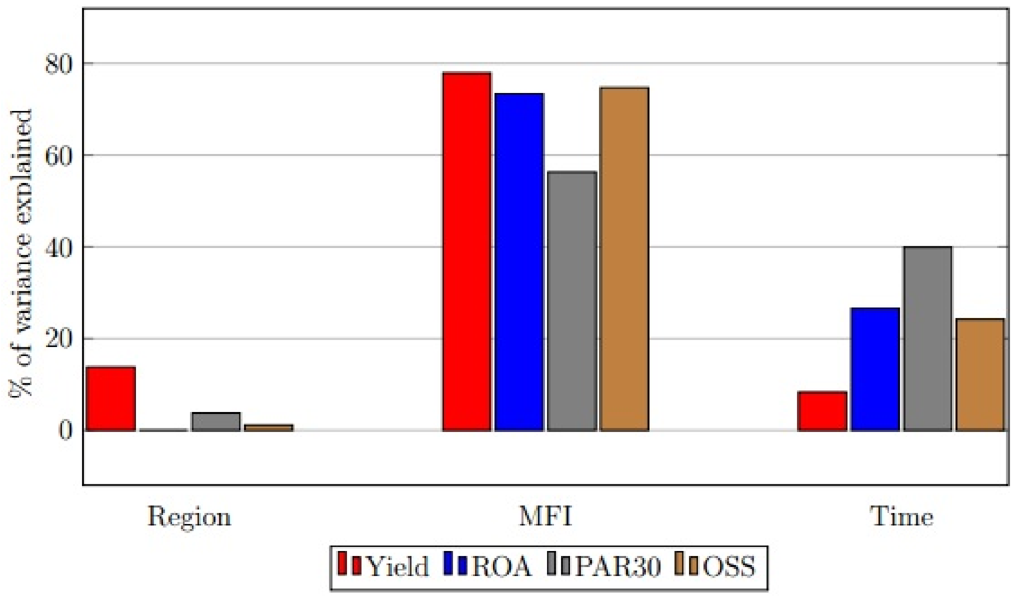

Table 3: Results from Small and Large MFIs subsamples estimation

	Dependent Variable: Yield on Gross Portfolio					
	Small MFIs			Large MFIs		
	M13	M14	M15	M16	M17	M18
Profit (1 = yes)	8.932*	11.17**	7.030*	4.039	3.682	3.645
	(3.626)	(4.311)	(2.959)	(3.087)	(2.877)	(3.739)
Constant	19.95***	1.348	21.52***	23.09***	21.79***	22.77***
	(1.961)	(8.753)	(2.139)	(3.661)	(7.647)	(3.031)
Variance Components						
Region level	0.526	40.798	0.000	49.322	75.045	46.041
	[0.28%]	[21.07%]	[0.00%]	[17.58%]	[30.73%]	[8.03%]
MFI level	168.863	140.669	129.569	209.991	148.280	187.043
	[89.93%]	[72.63%]	[94.30%]	[74.84%]	[60.72%]	[73.24%]
Time level	18.393	12.203	7.829	21.256	20.870	22.292

	[9.79%]	[6.30%]	[5.70%]	[7.58%]	[8.55%]	[8.73%]
Total variance	187.782	193.670	137.398	280.569	244.195	255.376
Observations	192	123	74	298	209	209
Control Variables	No	Yes	No	No	Yes	No
Matching	No	No	Yes	No	No	Yes

Std. Errors in parenthesis. Percentage of Variance explained in brackets. The control variables used were the same as the previous estimation. 1-to-1 nearest neighbor ps-matching was adopted. PS distribution shown at Fig.2, and balance at Table 4. ***p<.05 **p<.01 ***p<.001

Figure 2: Propensity Score Distribution

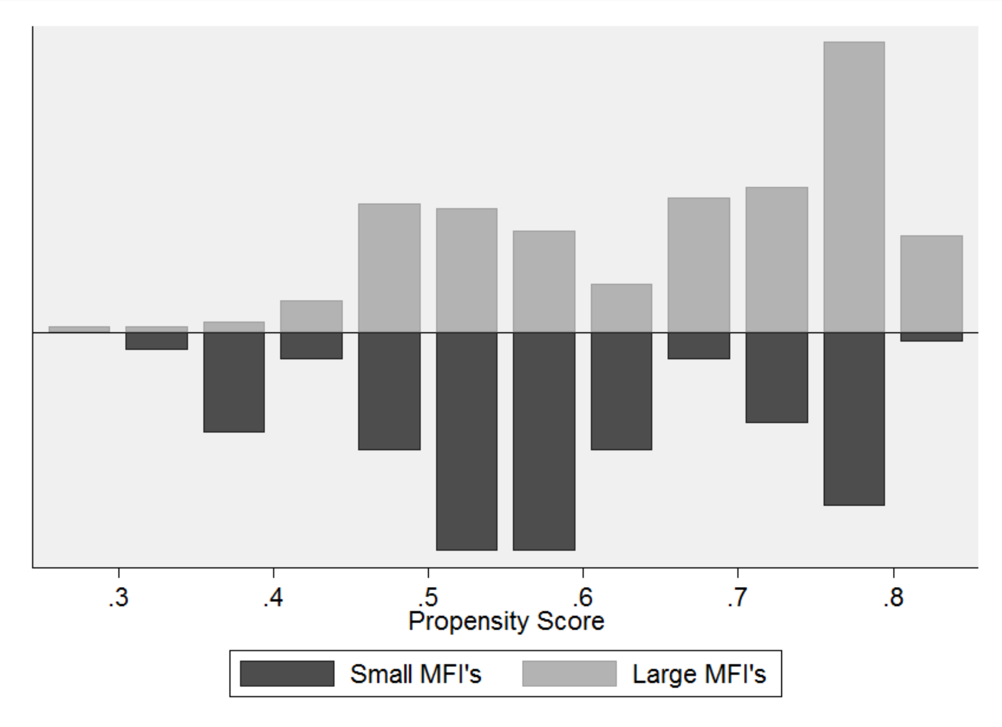

Table 4: Matching results

Variable	Un- vs. Matched	Mean Large	Mean Small	Mean diff.
Young	U	0.120	0.065	0.055
	M	0.120	0.129	-0.009
Mature	U	0.847	0.902	-0.055
	M	0.847	0.857	-0.010
% of Female Borrowers	U	0.720	0.581	0.139
	M	0.720	0.720	<0.001
Borrower Retention Rate	U	0.795	0.791	0.004
	M	0.795	0.749	0.046

Staff Turnover Rate	U	0.215	0.184	0.031
	M	0.215	0.227	-0.012

Figure 3: Bias reduction due to the propensity-score matching