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The Relationship between Competition and Borrowers Indebtedness: Empirical Evidence from South Asia

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Abstract

We investigate competition and its impact on borrowers' indebtedness (BI) in South Asian microfinance. Our empirical investigations are based on a comprehensive panel dataset of 355 MFIs located in seven countries in South Asia. The empirical results revealed that microfinance in South Asia is imperfectly competitive and the existing industry shows a monopolistic competition during the period under consideration. Also, the competition increased after the global financial crisis (GFC) in 2007–08 which implies that microfinance uses hostile lending behavior through the adverse selection that is highly risky and it can induce repayment crisis. The empirical findings also show that increased competition has significant negative effects on borrowers' indebtedness, particularly in large-scale and regulated microfinance organizations (MFIs). Instead of using equity financing, debt financing could be a better option. Finally, we find that while competition seems to have some positive effects in economic discourse by channeling technological improvements in products and services, its negative effects in microfinance outweigh the benefits over costs, particularly in poverty-stricken nations. The findings are helpful for the policymakers, microfinance industry, investors, borrowers, and Central Bank of South Asian markets.

Keywords: MFIs, Competition, Borrowers' Indebtedness, Microfinance, South Asia

JEL Classification Code: G02, B26, H74

1. Introduction

It is a widely accepted view that competition always ensures quality products and services, but in microfinance, the opposite is also true. Microfinance usually works in rural areas and small villages where the expansion of its services is limited to a few customers. That is why, severe competition amongst MFIs, operating in the rural periphery within the same borrowers creates adverse effects of competition. This unorthodox phenomenon could be justified for a number of reasons.

First of all, in competition, sustainability-oriented MFIs usually target relatively fewer poor borrowers to ensure timely repayments to minimize default risks. The selection of less poor borrowers excludes ultra-poor or poorest of the poor who direly need microfinance services more than anybody else because they live most of their time in poverty cycles that cannot be broken down without the help of microfinance. McIntosh and Wydick (2005) explained that the entry of new MFIs for existing borrowers reduces the potential profits of incumbent MFIs due to a reallocation of market shares that makes cross-subsidization difficult. Second, new MFIs usually adopt aggressive marketing to get significant market shares that have some serious repercussions. New MFIs overspread loans in existing borrowers without proper assessment of default risks in an information asymmetric environment. Some keen borrowers avail this opportunity and borrow from multiple sources. Srinivasan (2009) pointed out that 25 percent of all borrowers reportedly borrowed loans from more than six MFIs in India.

Assefa et al. (2013) stressed that the consequences of multiple borrowings (double-dipping) were so severe that the portfolio of €8.8 million of Indian microfinance had been in default for many years. Though competition in South Asian microfinance has significantly increased in the last few years with a parallel growth of microfinance, it paves the way for double-dipping which seriously endangers the

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sustainability of microfinance in South Asia. An increase in default rates coerces the MFIs to intermittently increase lending interest rates to equalize their operating income with expenses but sporadic changes in lending interest rates itself increase the risks of further default for a couple of reasons. First, a majority of MFIs work in rural areas where markets are small and income-generating opportunities are limited. Second, an increase in lending interest rates puts an extra burden of higher interest that deteriorates the ability to pay back. Poor become less subservient to pay, neither principal nor interest, and look to have some other sources to get money. In the majority of the cases, they attempt to use multiple borrowing sources to diversify extra liabilities. This kind of borrowing behavior triggers a negative chain reaction in the form of a repayment crisis.

The history of microfinance is not empty with such crisis just like in Bolivia in 1990 where aggressive moneylenders entered the market and attempted to grab a major market share of loans through aggressive marketing. A similar situation also happened in Bangladesh in 1999. Aghion and Morduch (2010) reported that the estimated 15 percent of all borrowers took loans from at least more than one institution in ninety-five percent of eighty villages surveyed. The repayment crisis in Bangladesh was so severe that Grameen Bank's reported repayment rates were drastically declined from above 98 percent to below 90 percent. The other crises of the same nature occurred in Kenya in 2003, and in Zambia in 2008–09. Guerin et al. (2014) pointed out that so many countries in the world have faced such kind of repayment crises, like Nicaragua, Bosnia Herzegovina, Pakistan, and Morocco in 2007 and India (in some southern parts) in 2009.

One of the root causes of the repayment crisis is double-dipping which intimidates the financial sustainability of MFIs, and if outreach is increased to a majority in the market then the microfinance repayment crisis is inevitable. So what causes the borrowers to behave in such manners that put microfinance's sustainability at risk? We found that primary screening or borrowers' selection plays an important role in this borrowing behavior. Microfinance is considered a highly risky business without the guarantee of collateral, in comparison with the banking system where loans are collateralized; therefore, the borrowers' selection is much more difficult in microfinance especially in an information asymmetric environment. There are no uniform criteria to assess borrowers; at present, various risk assessment tools are being used for screening. As a common practice, the interest rate is used as a proxy to screen out good borrowers from bad ones.

The borrowers' selection through the yardstick of interest rates has some other complications. As a security measure, lenders charge exorbitant interest on highly risky loans in high-risk high-return business domains but high interest itself increases the risk of default. Stiglitz and Weiss (1981) illustrate this point that different borrowers have different probabilities of repayment which change with respective changes in interest rates. The method of solidarity loans or group lending (started by Muhammad Yunus of Grameen Bank, Bangladesh) is a possible solution to prevent default crises. Although group lending was successfully employed in Bangladesh and acknowledged by the world, it has some serious complications. For instance, weak intra-group coordination stimulates the whole group to default. If the leader of the group shows reluctance to repay the loans on time, other group members follow the same behavior. In most cases, the poorest member of the group default first because usually poor members are highly influenced by the leader of the group and if the group leader sets a wrong precedent then it is certain that the poorest members take it for granted.

Sinha (2009) found a higher incidence and period of default among poorer borrowers. In the southern sample, more than 38 percent of the poorest have dues for more than 12 months, compared with an average of 28 percent across other wealth ranks. What causes the poor to opt to default? The answer lies in the fact that the poor are more susceptible to exogenous shocks, which frequently occur in their lives, and they used to deal with such shocks with different ways of financial management. The financial methods poor usually used include informal borrowing (neighbors, family, friends, etc.), and selling of livestock and valuables (Alshammari et al., 2020). But the inception of microfinance has changed the way to handle financial shocks. Borrowing from microfinance becomes an easy option for the poor to generate quick income during hard times. In that case, microloans are used not for income-generating activities but for consumption purposes only. Such ill-conceived financial decisions create a number of problems for the poor. First and foremost, poor people are not able to generate and save funds quickly because their working capital always remains negative during their entire lifetime. In such miserable conditions, they can't generate enough funds to escape catastrophe-led poverty shocks. The current wave of microfinance based financial-inclusion resolves the issues of fund generation without collateral requirements.

However, the ease of microfinance loans doesn't make their life easy because in hard times they collect money through borrowing from as many sources as they can which becomes the starting point of their troubles. Borrowing from multiple sources puts immense psychological pressure both from the MFIs and the community as well in the case of group lending. Repayment to more than one MFIs without savings makes their lives vulnerable, and most of the time they pay neither interest nor principal. Then, the MFIs initiate harsh recovery proceedings against the defaulters to get their outstanding loans back. It coerces them to borrow from other available sources to repay the first lender to escape from the default cycle. But, this strategy only increases their financial problems and does not provide any help to break the web of loans. In group lending, it is obvious that if a group member defaults then other members are responsible to pay back loans on his behalf.

We are induced to conduct this study because these issues are growing in time with a parallel growth of microfinance in South Asia. Therefore, this timely activity is an attempt to get the impact of competition on borrowers' indebtedness which is a key element in repayment crisis. Our objective is to get empirical evidence regarding the paradoxical nature of competition and to test the hypothesis that intensifying competition in microfinance can provoke a repayment crisis. Nevertheless, borrowers' indebtedness (BI) can hit the sustainability of microfinance. It is obvious that fragile microfinance could not address the long-standing issues of poverty alleviation. The hypothesis for this study is that the intense microfinance competition increases the borrowers' indebtedness. Obviously, when microfinance competition intensified, newly entrant MFIs aggressively target relatively fewer poor borrowers for a number of reasons. First, to get a rapid increase in the loans portfolio. Second, to grab a strong position in the microfinance market with the presence of existing MFIs. Last but not least, they attempt to show quick success to attract grants and subsidiaries from donor agencies. To fulfill these objectives, newcomers prefer to enter established markets (where already screened borrowers are available) to keep their start-up cost low at the expense of market concentration. Such concentrated microfinance markets make the microfinance environment where too many lenders chase too few borrowers.

To the best of our knowledge, the competition in microfinance and its impacts on BI has never been analyzed before; therefore, this study aims to fill that gap. This paper is organized in a way that section 2 documents the past literature on competition in microfinance and banking, section 3 describes theoretical background, section 4 shows data and methodology, section 5 presents empirical results, and section 6 is based on our conclusions.

2. Literature Overview

The assessment of competition and its effects on BI is important in the determination of the role of microfinance in poverty alleviation. Donor agencies are usually concerned whether their funds are properly used in poverty alleviation via microfinance or not. The existing material on the current topic is scarce because the issue of competition and its effects on BI has not been documented exclusively. Therefore, we had no choice except to use some of the indirect literature which is relevant and noteworthy. McIntosh and Wydick (2005) analyzed the link between increasing competition and the entry behavior of newcomers in microfinance sector of Uganda. They did not find any positive connection between market competition and expansion of outreach amongst MFIs operating in rural areas of Uganda. It is pointed out that incumbent MFIs show reluctance in scale expansion due to either inaccessibility or limited financial ability.

McIntosh and Wydick (2005) pointed out that intensified competition in loans markets drop-out poorer borrowers from the markets (AsadUllah, 2021a, 2021b). Ghosh and Van-Tassel (2011) asserted that outreach expansion can improve the overall trust of donors and they may join poverty alleviation efforts with grants and subsidiaries. The microfinance competition enhances when MFIs compete for portfolios without caring about the rules of the game. Double-dipping seriously hurts the financial position of new MFIs when they enter established markets. Market concentration lowers market shares and increases the operational cost of business.

Guha and Chowdhury (2013) assert that the implications of competition on lending interest rates are imprecise. The interest rates are increased with an increase in default rates because the burden of extra losses (due to default) is shared upon existing borrowers through increased interest rates. However, in some cases, the interest rates can be reduced due to business-stealing effects that increase with the intensity of competition. The study of Baquero et al. (2012) covered 379 microcredit providers in 67 countries from 2002 to 2008. They found multiple effects of competition on the performance of different loan providers according to the nature of the business. The 'profit-motive banks' (PMBs) in a competitive environment are most efficient because they charge low interest and practice better risk mitigation. The effects of competition on 'non-profit banks' (NPBs) are insignificant because of low-interest elasticity. However, an increasing number of PMBs upsurge delinquency rates of NPBs as borrowers of NPBs voluntarily default to shift to emerging PMBs due to aggressive marketing. Assefa et al. (2013) applied 'price cost markup' (PCM) and Lerner Index on the data of 362 MFIs situated in 73 countries. They conclude that highly competitive microfinance markets downgrade the performance of MFIs. The inefficiency of microfinance is caused by the intensity of microfinance competition. They iterate that without improvement lending standards efficiency of the microfinance market is difficult.

There is no bi-directional causality between efficiency and competition because a unidirectional causality runs from competition to efficiency but not vice versa (Mkrtchyan, 2005; Casu & Girardone, 2010; Johnes et al., 2009). The 'Panzar and Rosse' (PR) model is used by Gischer and

Stiele (2009) on savings banks of Germany; they assert that high competition adversely affects the market and created more concentration in the German banking industry. Hamza (2011) has also used the PR model to assess the impact of competition on the banking industry of Tunisia. He found negative consequences of competition in the Tunisian banking industry. Van-Leuvensteijn et al. (2011) used the Boone (2004) Indicator model to get the evolution of competition in loans markets in eight European countries. They conclude that the effects of competition differ according to the nature of institutions and socioeconomic conditions of the country.

The scrutiny of previous literature revealed that competition could have negative implications in microfinance. It can deteriorate the overall efficiency of microfinance because both stakeholders in microfinance disturb the system at their own level. The lenders relax the grip through adverse selections, and hostile marketing, and borrowers misuse the opportunity of swift loans through manipulation of double-dipping. Inconsistent behavior of all stakeholders in a competitive environment can intimidate repayment shocks. As a preventive approach, it is fairly adequate to get the competition and its effect on BI. Although, the financial performance of MFIs was previously measured through the effects of competition on financial sustainability. This is quite valid because financial sustainability assesses the capability of revenue generation to cover financial costs for less dependency on external subsidization. A direct link between competition and BI has yet to establish which is our aim in this paper.

3. Theoretical Background

The assessment of competition can be done through two mainstream approaches i.e. structural and non-structural. The structural view consists of two major leaves; Efficient Structure Hypothesis (ESH) and Structure Conduct Performance (SCP). The SCP introduced by Mason (1939) and Bain (1951), focuses on the degree of competition in an industry by looking at its structure. It provides a direct relationship of the firms' performance with the industry structure. Application of SCP paradigm entails that in the banking sector, highly concentrated markets provide a monopolistic position to reap abnormal profits by getting large spread margins and market powers. They enjoy their position knowing the fact that the regulations and institutionalized barriers would not allow the new entrant to get into the business and threaten their position. Nevertheless, the SCP paradigm has its own shortcomings and loopholes, it has widely been used in industrial organizations for the purpose of competition assessment. Figure 1 shows the flow diagram of Structure Conduct Performance.

In contrast with SCP, the Efficient Structure Hypothesis gives all credit to the performance of the firms rather than the structure of the industry. In the ESH, the order of market power attainment is reversed i.e. performance of the firm provides the market leadership. The factors behind the efficiency of the firm might have the Research & Development (R&D) activities, cutting edge expertise, managerial intelligence, and higher labor productivity, etc. Efficient firms gain market share over inefficient ones which increases the concentration in the industry (Catena, 2000).

4. Data and Methodology

4.1. Data

The dataset for this study is constructed by compiling the data of 355 MFIs located in seven countries in South Asia for the period 2003 to 2011. All data is collected through 'microfinance information exchange' (MIX market) expect GDP growth which has been collected from the World Development Indicators of the World Bank. All three-factor costs are calculated as the ratio of capital expenses to the net fixed asset, interest expenses paid for borrowing to total borrowings, and personnel expenses to the number of employees respectively. The total assets include tangible fixed assets and non-fixed assets. The interest income includes interest earned on loans and the total income includes interest income as well as non-interest income. The proxy variable used to measure the size of the firm is the number of employees. The equity-to-assets ratio is calculated as total equity to total assets. The proxy used for non-performing-loan is loan loss rate, and for scale effects, returns on assets and returns on equity is used. The values of all data series are in the US dollar. Table 3 shows the summary statistics of all the variables used in this study.

4.2. Handling Inconsistencies in Data

To handle inconsistencies in reporting of data and missing values we have reduced our sample period from 2003 to 2011 instead of 1997 to 2012. Inter Alia, MFIs who failed to report in two consecutive years were deleted from our final sample. The initial sample consists of 386 MFIs' data but we reduced our sample by 29 MFIs' to minimize the impact of inconsistencies and missing values in data, so our final dataset contains the data of 355 MFIs, located in seven countries in South Asia.

4.3. Empirical Application

An alternative approach to the production function is the cost function methodology. The usage of the cost function methodology is more appropriate than the production function methodology because it incorporates the behavioral relationships via cost minimization.

We start from the general form of the translog cost function for n input and m output:

$$\operatorname{In} C = \alpha_0 + \sum_{i=1}^{n} \alpha_i \operatorname{In} p_i + 0.5 \sum_{i=1}^{n}\sum_{j=1}^{m} \alpha_{ij} \operatorname{In} p_i \operatorname{In} p_j + \sum_{i=1}^{m} \beta_i \operatorname{In} q_i + 0.5 \sum_{i=1}^{n}\sum_{j=1}^{m} \beta_{ij} \operatorname{In} q_i \operatorname{In} q_j + \sum_{i=1}^{n}\sum_{j=1}^{m} \delta_{ij} \operatorname{In} p_i \operatorname{In} q_j \quad (1)$$

Where ln(C) is the log of the total cost of production, ln (p_i), (p_j) are the log of prices, and ln (q_i), (q_j) are the log of quantities. While α, β and δ are the estimation parameters.

For a single output q with n input factors of price p_i (i = 1 to n):

$$\operatorname{In} C = \alpha_0 + \sum_{i=1}^{n} \alpha_i \operatorname{In} p_i + 0.5 \sum_{i=1}^{n}\sum_{j=1}^{m} \alpha_{ij} \operatorname{In} p_i \operatorname{In} p_j + \alpha_q \operatorname{In} q \quad (2)$$

To estimate the potential scale effects:

$$\operatorname{In} C = \alpha_0 + \alpha_q \operatorname{In} q + 0.5\,\alpha_{q^2} + \operatorname{In} q^2 + \sum_{i=1}^{n} \alpha_{iq} \operatorname{In} p_i \operatorname{In} q + \sum_{i=1}^{n} \alpha_i \operatorname{In} p_i + 0.5 \sum_{i=1}^{n}\sum_{j=1}^{m} \alpha_{ij} \operatorname{In} p_i \operatorname{In} p_j \quad (3)$$

(Where $\alpha_{ij} = \alpha_{ji}$)

To satisfy the condition of linear homogeneity in input prices

$$\sum_{i=1}^{n} \alpha_{iq} = 0$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} \alpha_{ij} = 0$$

$$\sum_{i=1}^{n} \alpha_i = 1$$

To get the cost share of i^{th} input, we take the partial derivative of equation (3) w.r.t. log of pi:

$$Si = \frac{\partial \operatorname{In} C}{\partial \operatorname{In} pi} = \alpha_i + \alpha_{iq} \operatorname{In} q + \sum_{j=1}^{m} \alpha_{ij} \operatorname{In} p_j \quad (4)$$

If we take the partial derivative of equation (3) w.r.t. q then we have an equation that measures the effect of scale economy i.e.

$$\frac{\partial \operatorname{In} C}{\partial \operatorname{In} q} = \alpha_q + \sum_{i=1}^{n} \alpha_{iq} \operatorname{In} p_i + \alpha_{q^2} \operatorname{In} q \quad (5)$$

This shows the elasticity of cost w.r.t. output.

$$\frac{\partial \operatorname{In} C}{\partial \operatorname{In} q} = \frac{\partial C}{\partial q}\frac{q}{C} = \varepsilon_c \quad (6)$$

The profit-maximizing condition in a competitive environment depends upon:

$$\overline{R_i}(Y_i, Z_i, n) = \overline{C_i}(Y_i, W_i, J_i) \quad (7)$$

Where $\overline{R_i}$ and $\overline{C_i}$ the marginal revenue and marginal cost of the firm i, Y_i is the output, n is the number of the firms in the industry, is a vector of factor input prices of firm i, Z_i and J_i are exogenous vectors that shift firms' revenue and cost functions respectively.

In Panzar and Rosse model's H-Statistics, the factor price elasticities are used to regress the reduced form revenue. Empirically:

$$\operatorname{In} R_{it} = \alpha_0 + \sum_{i=1}^{n} \beta_i \operatorname{In} p_i + \gamma_q \operatorname{In} q \quad (8)$$

Where ln R_{it} is the reduced form revenue of firm i in time t, and the right-hand side terms is the elasticity of input factor prices.

For the empirical estimation of the H-Statistics, we use the following equation

$$\text{Ltinc}_{it} = \beta_0 + \beta_1 \text{Llbr}_{it} + \beta_2 \text{Lcap}_{it} + \beta_3 \text{Lfnd}_{it} + \beta_4 \text{Last}_{it} + \beta_5 \text{Lsiz}_{it} + \varepsilon_i \quad (9)$$

Where the dependent variable Ltinc is a log of the ratio of total income to total asset and the regressors include a log of the unit cost of labor (llbr), capital (lcap), and fund (lfnd). To measure the scale effect, we used a log of the total asset (last) and a log of the size of MFIs (lsiz). All the β_S are parameters of estimation and ε is the stochastic error term.

$$H : \sum_{i=1}^{n} \beta_{ij} <= 0 \quad (10)$$

$$H : \beta_1 + \beta_2 + \beta_3 <= 0 \quad (11)$$

Under the constraints established by the PR model, the sum of the factor price elasticities of a monopolist's reduced form revenue equation must be non-positive because it explicates the inverse relationship. Farther the input prices increase lesser the revenue a monopolist can attain due to the similar increase in the marginal cost.

$$H : \sum_{i=1}^{n} \beta_i \tag{12}$$

$$H : \beta_1 + \beta_2 + \beta_3 = 1 \tag{13}$$

In contrast with the above, the rejection of a non-positive value of H shows the competitive position of the firm in an industry. According to the second proposition of the PR model, the sum of the factor price elasticities of the firms in the long-run competitive environment equals unity. This enforces that a change in factor prices would change the marginal cost with the same magnitude accordingly. For the sustainability of the firm, an adjustment in the quantity is required while keeping the marginal revenue at a similar point to the marginal cost (Table 1).

$$\begin{aligned}\text{Linc}_{it} &= \beta_0 + \beta_1\text{Llbr}_{it} + \beta_2\text{Lcap}_{it} + \beta_3\text{Lfnd}_{it} \\ &\quad + \beta_4\text{Last}_{it} + \beta_5\text{Lsiz}_{it} + \varepsilon_t\end{aligned} \tag{14}$$

Where linc shows the ratio of interest income to the total asset as a dependent variable implying the condition that interest income is the main source of earning for microfinance institutes.

On the other hand, some of the MFIs provide banking facilities also and have fee-based incomes which are reflected in equation (9). The independent variables include factor prices of inputs i.e. lbr, cap, and fnd as the unit cost of labor, capital and fund respectively. All the variables are in logarithmic form. To get the scale effect we used MFIs specific factors like total assets and size (measured through a number of employees).

$$\begin{aligned}\text{Lroa}_{it} &= \beta_0 + \beta_1\text{Llbr}_{it} + \beta_2\text{Lcap}_{it} + \beta_3\text{Lfnd}_{it} \\ &\quad + \beta_4\text{Last}_{it} + \beta_5\text{Lsiz}_{it} + \varepsilon_t\end{aligned} \tag{15}$$

To check the robustness of the estimated models we used return on assets as a dependent variable while keeping the other regressors the same.

Table 1: Interpretation of *H* Statistics of PR Model

***H* Statistics**	**Competitive Environment Test**
$H \le 0$	Monopoly equilibrium
	Perfect colluding oligopoly
	Conjectural variations short-run oligopoly
$0 < H < 1$	Monopolistic competition free entry equilibrium
$H = 1$	Perfect Competition
	Natural monopoly in a perfectly contestable market
	Sales maximizing firms subject to the breakeven constraint
Equilibrium Test	
$H < 0$	Disequilibrium
$H = 1$	Equilibrium

Source: Chun and Kim (2004).

4.4. Impacts of Competition on Borrowers-Indebtedness (BI)

To empirically investigate the impacts of competition on BI, the following regression equation is used in consideration that competition and BI are determined simultaneously.

$$\text{BI}_{it} = \alpha_0 + \beta_0\text{COM}_{it} + \sum \gamma_i Z_{it} + \varepsilon \tag{16}$$

Where BI represents borrowers' indebtedness measures through loan loss rates, COM represents competition and variable Z_{it} represents a set of control variables.

In previous literature, competition is measured through the number of MFIs in the market without considering the scale effects and differences in institutional characteristics. However, this study investigates competition by using H-statistics and Boone indicator considering the scale differences and institutional framework. For this purpose, another variable BI is developed i.e. H-statistic is multiplied by the ratio between the total number of MFIs in the market and the number of active borrowers because we assume that intensified competition increases the probability of borrowers' indebtedness. The control variables include cost, technology, and financial factors. First of all, the total cost is used to measure the effects of costs. A high operational cost coerces the MFIs to increase their loans portfolio to generate additional revenues that can cover extra costs. Eventually, in search of growth in loans portfolio, they intentionally use adverse selection which increases the risks of default. Therefore, we expect that high costs give a higher value to BI. Secondly, to get the impacts of technology, the size of MFIs (measured through the number of employees) is used as a technological factor. It is assumed that large MFIs are more technologically sophisticated than their smaller counterparts. They use better management practices, have sound financial and material resources, and maintain better information systems; therefore, technological factors are expected to be correlated negatively with BI. Third, to get the impact of financial factors, total assets and 'equity-to-assets' (ETA) ratios are used which are expected to be correlated negatively with BI because better assets management and ETA provide financial leverage to firms.

4.5. The Data and Variables

The dataset is constructed by compiling the data of 354 MFIs located in six countries in South Asia for the period 2003~2011. The data is collected through 'microfinance information exchange' (MIX) which is U.S. based data service provider. Three variables are calculated for factor input prices i.e. ratio of capital expenses to the net fixed asset (unit cost of capital), interest expenses paid for borrowings (unit cost of funds), and personnel expenses to the number of employees (unit cost of labor). Total assets include tangible fixed assets and non-fixed assets. Interest income includes interest earned on loans, and total income includes interest income plus non-interest income. The proxy variable to measure the size of MFIs is the number of employees. The ratio of equity-to-assets is calculated as total equity to total assets, and the proxy variable for borrowers' indebtedness is the loan loss rate. The dummy variables are used for scale, self-sufficiency, regulatory framework, and legal status. All values are represented in US dollar except indicated otherwise. The summary statistics of variables is exhibited in Table 2. ROA, ROE also employed as a variable as supported by AsadUllah (2017).

5. Empirical Results

The competition is assessed by the PR model and the H-statistics (collected through the PR model) is used to compute the partial factors of competition intensity. The empirical estimation is based on panel regression instead of 'ordinary least squares' (OLS) to a cross-section data of 354 MFIs for the period 2003–2011. One of the main

Table 2: Summary Statistics of the Variables

Description	Variables	Formation	Unit	Mean	Median	Std. Dev.	Skewness
Total Assets	*A*	Total Assets	US$	18864184	1774669	87608884	10.200
Output	*Q*	Gross Loan Portfolio	US$	16706326	1497704	71028629	8.092
Total Cost	TC	Operating Cost+ Non-Operating Cost	US$	6721432	611029	29635435	8.83
Cost of Capital	*K*	Capital Cost-to-Net Fixed Assets	–	–2.284	–0.150	28.386	–4.890
Equity/ Asset Ratio	*E*	Total Equity / Total Assets	–	2.369	0.150	12.027	5.319
Unit Fund Cost	*F*	Interest Cost/ Total Borrowing	–	0.099	0.080	0.143	10.696
Interest Income/ Assets	IR	Interest Income / Total Assets	–	0.168	0.140	0.183	7.246
Unit Labour Cost	*L*	Personnel Cost/ No. of Employees	–	2062.544	1667.930	1421.751	1.804
Loan Loss Rate	LL	Loan Loss Rate	–	0.434	0.020	2.983	29.638
Total Income/ Total Assets	TR	Total Income/ Total Assets	–	0.273	0.210	0.269	7.092
Returns on Assets	ROA	Returns on Assets	%	–0.020	0.020	0.299	–12.260
Returns on Equity	ROE	Returns on Equity	%	0.272	0.120	5.100	31.707
Economic Growth	GDP	GDP Growth	%	6.749	6.240	3.320	1.891
Size of the Firm	*S*	No. of Personnel	No.	527.000	84.000	2174.699	8.855
Self Sufficient	SS	Dummy	1 = Self-sufficient; 0 = Otherwise				
Regulated	*R*	Dummy	1 = Regulated; 0 = Otherwise				
Scale	*S*	Dummy	1 = Small; 2 = Medium; 3 = Large				
Legal Status	LG	Dummy	1 = NGO; 2 = Bank; 3 = NBFI; 4 = Otherwise				

advantages of using panel regression is that it gives more accurate inferences of parameters by keeping more variability in the sample with a high degree of freedom. The panel regression is quite appropriate to test the dynamic relationships due to better control for omitted variable bias (Hsiao, 2007). Three different models are used to assess competition with different dependent variables i.e. total income, interest income, and ROA. 'Fixed effects' (FE) estimation is employed based on the significant rejection of the null hypothesis by the Hausman Test that the 'random effects' (RE) estimation is consistent and efficient. The regression results are displayed in Table 3.

The Boone Indicator model is also applied to capture the evolution of competition with the passage of time because we assume that competition is not a time-invariant phenomenon. The empirical results confirm that the competition has intensified in South Asian microfinance during the period under consideration. The results for the evolution of competition are shown in Table 4.

The empirical analysis also measures the impacts of GFC (2007–08) on microfinance in South Asia. Fixed Effect estimation is used based on the Chow test which confirms structural breakup in our dataset. The estimates of the Chow test and the testing of competition are presented in Table 5.

Table 3: Regression Results of the Competition In Microfinance Sector In South Asia

Independent Variables	**Dependent Variables**					
	TR		**IR**		**ROA**	
	Fixed Effects	**Random Effects**	**Fixed Effects**	**Random Effects**	**Fixed Effects**	**Random Effects**
Intercept	–5.464*	–4.973*	–4.544*	–4.555*	–0.499*	–0.124
	(0.528)	(0.528)	(0.412)	(0.333)	(0.143)	(0.103)
Log(*L*)	0.179*	0.179*	0.133*	0.167*	0.017	–0.017
	(0.054)	(0.039)	(0.042)	(0.03)	(0.014)	(0.010)
Log(*K*)	–0.046*	–0.036*	0.007	0.005	–0.008	–0.009
	(0.018)	(0.015)	(0.014)	(0.012)	(0.005)	(0.010)
Log(*F*)	0.400*	0.221*	0.270*	0.153*	0.019	0.010
	(0.060)	(0.045)	(0.047)	(0.037)	(0.016)	(0.011)
Log(*Q*)	0.125*	0.101*	0.102*	0.086*	0.001	0.001
	(0.017)	(0.014)	(0.013)	(0.011)	(0.004)	(0.004)
Log(*A*)	0.055*	0.037*	–0.005	–0.015	0.023*	0.013*
	(0.021)	(0.018)	(0.016)	(0.015)	(0.005)	(0.004)
Log(*S*)	0.208*	0.113*	0.190*	0.141*	0.008	–0.0007
	(0.033)	(0.026)	(0.025)	(0.021)	(0.009)	(0.009)
$\overline{R_i}$	0.69	0.15	0.75	0.13	0.61	0.17
H statistic	0.533	0.270	0.410	0.325	0.028	0.010
Wald statistic	1158.525	1721.123	1785.096	2403.100	1785.096	25831.1
H = 1	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Wald statistic	24.344	20.017	17.423	16.546	17.423	2.940
H = 0	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.032]
Hausman Test	–	142.300	–	90.735	–	36.961
		[0.000]		[0.000]		[0.000]
Observations	3186	3186	3186	3186	3186	3186

Note: Log (*L*), log (*K*) & log (*F*) represent log of unit cost of labor, capital and fund, while log (*Q*) log (*A*) & log (*S*) represent log of output, assets and size respectively. We used 'fixed effects' (FE) panel estimation on the basis of Hausman Test. ( ) represent standard errors, [ ] show *p*-values & *, **, *** exhibit significance level at 1%, 5% and 10% respectively.

Table 4: Evolution of Competition Over Time (Boone Indicator)

Years/Country	Afghanistan	Bangladesh	India	Nepal	Pakistan	Sri Lanka
2003	–0.0411	–0.0221	–0.0231	–0.0412	–0.0323	–0.0472
2004	–0.0421	0.0183	0.0172	–0.0007	0.0075	–0.0073
2005	–0.0433	0.0173	0.0163	–0.0008	0.0073	–0.0075
2006	–0.0391	0.0222	0.0201	0.0038	0.0113	–0.0035
2007	–0.0381	0.0224	0.0212	0.0039	0.0120	–0.0027
2008	–0.0372	0.0232	0.0223	0.0046	0.0128	–0.0020
2009	–0.0392	0.0221	0.0212	0.0035	0.0117	–0.0031
2010	–0.0386	0.0231	0.0214	0.0041	0.0123	–0.0026
2011	–0.0392	0.0223	0.0212	0.0031	0.0113	–0.0035

Note: The table represents the estimates of the Boone indicator from equation (3). The dependent variable, log (ROA) is regressed on marginal cost derived from the Translog cost function in equation (4) using 'fixed effects (FE) estimation based on the Hausman test.

Table 5: The Estimates of Competition

Testing for Competition (*H*-Statistics)						
$H_0 = \beta_1 + \beta_2 + \beta_3 = 1$ (Perfect Competition) $H_1 = \beta_1 + \beta_2 + \beta_3 \neq 1$						
Dependent Variable	**TR**		**IR**		**ROA**	
Period	**Pre GFC**	**Post GFC**	**Pre GFC**	**Post GFC**	**Pre GFC**	**Post GFC**
Test statistics	0.317	0.460	0.272	0.374	0.245	0.015
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0
Market Structure	Monopolistic Competition		Monopolistic Competition		Monopolistic Competition	
Alternative Test (Wald test of zero restriction)						
$H_0 = H = 1$ (Perfect Competition)						
Test statistics	982.428	995.395	1554.999	1467.767	1574.595	12113.3
p-values	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0
Market Structure	Monopolistic Competition		Monopolistic Competition		Monopolistic Competition	
$H_0 = H = 0$ (Monopoly)						
Test statistics	04.759	19.976	6.787	12.041	5.580	1.009
p-values	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.387)
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Accept H_0
Market Structure	Monopolistic Competition		Monopolistic Competition		Monopolistic Competition	Monopoly

Note: The table shows the results of three different models i.e. TR exhibits total revenue, IR shows interest revenue, and ROA indicates return-on-asset. The regression is based on equation (5) by following the PR model. The hypothesis of perfect competition is based on the first proposition of the PR model which requires the H-statistics to be equal to unity. The Chow test and F-test are used to get the structural breakup and joint significance in our dataset. The H statistics and the Wald tests reject the null hypothesis of perfect competition and monopoly before and after GFC in all three models except in model 3 where the Wald test shows the market structure as a monopoly.

The empirical results suggest that the intensity of competition is increased after (GFC); hence, it could be argued that business opportunities in the post-GFC period attracted new MFIs to enter with high expectations of potential profits. New MFIs choose to penetrate established markets to minimize their startup cost. Although this strategy provides them better screening opportunities without incurring additional costs it also increases the probability of double-dipping and default. The regression results of Pre-GFC and post-GFC estimates are presented in Table 6.

The equation (6) is used for empirical estimation to get the impacts of competition on BI. The results indicate that competition significantly increases borrowers' indebtedness at small scale, regulated, and self-sufficient MFIs especially NGOs and banks. It seems that small NGOs and banks are more eager to get larger shares of loans. The competition parameters are insignificant for non-regulated MFIs which implies that non-regulated MFIs uphold market position by keeping the focus on existing customers only. At a medium scale, the competition has positive impacts except for non-regulated and not self-sufficient MFIs. Insignificant competition implies that those MFIs do not have strong financial backups for outreach expansion. Nevertheless, at a large scale, competition is significant for all categories (regulated/ non-regulated and self-sufficient/ not self-sufficient) indicating serious implications on BI. It seems that large-scale MFIs extensively compete for market shares because it is an issue of market dominance and portfolio growth.

For regulated NGOs and banks, the empirical results for control variables demonstrated that MFI size has a significant negative impact on BI. For credit unions and rural cooperatives, however, size is insignificant. It demonstrates how an expanded information system minimizes the risk of default as the company grows in size. Though a few size parameters are important for different types of MFIs, they could not be considered due to inconsistencies in the relationships. For small-size MFIs, the empirical results for technological factors are insignificant and inconsistent. For medium and large-scale MFIs, the parameters of technological factors are significant and negatively linked with BI. The negative relationship indicates that the issues of double-dipping and multiple borrowings can be resolved through technological progress. The cost factors are also included with the expectations of their positive links with BI. The empirical results exhibit that at a small scale, the parameters of total costs are significant but have inconsistent relationships; also, the cost parameters are insignificant at medium and large scales. Therefore, this study couldn't find a direct link between the factor cost and BI. The equity to asset ratio is expected to be correlated positively with BI. The results indicate that financial factors have significant positive effects on BI for regulated MFIs except for banks. It implies that focusing on financial leverage is inappropriate and the use of equity financing could increase the default rates.

6. Conclusion

An acute competition in microfinance increases the risk of borrowers' indebtedness which seriously endangers the sustainability of the whole system of microfinance. In that context, we investigated competition and its impacts on borrowers' indebtedness. The empirical investigation revealed that South Asian microfinance is a case of monopolistic competition (*H*-Statistics estimates); and, the degree of competition has evolved and intensified over time (Boone Indicators estimates). Also, microfinance in South Asia was quite responsive to the global financial crisis as the results confirmed a significant increase in the competition after GFC (2007–08). The Chow test is conducted to get the confirmation of structural breakup in data. The empirical results indicate that the intensity of competition is significantly increasing the risk of borrowers' indebtedness, especially for largescale regulated MFIs. At this scale, largescale MFIs struggle to acquire more and more market shares to get rapid portfolio growth. To get this, the borrower's selection criteria is relaxed that increases adverse selection. In a highly asymmetric information environment, a lexical selection of borrowers with inconsistent follow-ups, and a lack of control on borrowers' financial activities increase the likelihood of high defaults. The estimation results for technological factors show significantly negative effects on borrowers' indebtedness which implies that technologically efficient MFIs can use better selection methods to curtail the cost per loan. Technical efficiency provides cost control that eventually increases the profits which can be used poverty alleviation through cross-subsidization. The financial factors have significantly negative effects on BI; it is, therefore, suggested that large-scale MFIs should not use financial leverage to attract donor agencies. Instead of using equity financing, debt financing could be a better option. Finally, we conclude that competition seems to have some positive effects in economic discourse as it channels through technological improvements in products and services but in microfinance, its adverse effects outweigh the benefits over costs, especially for poverty-hit countries.

Table 6: Regression Results for The Implications of Global Financial Crisis (GFC-2007-08) On Microfinance In South Asia

Explanatory Variables	Dependent Variables					
	TR		IR		ROA	
	Pre GFC	Post GFC	Pre GFC	Post GFC	Pre GFC	Post GFC
Intercept	–4.831*	–4.447*	–3.568*	–4.438*	–0.369*	–0.605*
	(0.567)	(1.092)	(0.445)	(0.801)	(0.158)	(0.285)
FD	No	0.384	No	–0.870*	No	–0.236
		(0.455)		(0.356)		(0.127)
Log(*L*)	0.092	0.169	0.028	0.140	0.226	0.006
	(0.059)	(0.097)	(0.046)	(0.076)	(0.016)	(0.027)
Log(*L*).FD	No	0.076	No	0.112*	No	0.005
		(0.038)		(0.030)		(0.010)
Log(*K*)	–0.0002	–0.083	0.023	–0.007*	–0.011*	–0.006*
	(0.019)	(0.038)	(0.015)	(0.030)	(0.005)	(0.014)
Log(*K*).FD	No	–0.082	No	–0.031*	No	0.005
		(0.018)		(0.014)		(0.005)
Log(*F*)	0.225*	0.374*	0.221*	0.241*	0.030	0.015
	(0.068)	(0.122)	(0.054)	(0.095)	(0.019)	(0.034)
Log(*F*).FD	No	–0.082*	No	0.020	No	–0.015
		(0.018)		(0.041)		(0.015)
Log(*Q*)	0.078*	0.097*	0.063*	0.124*	0.002	0.006
	(0.019)	(0.038)	(0.015)	(0.030)	(0.005)	(0.010)
Log(*Q*).FD	No	0.018*	No	0.060*	No	0.004
		(0.019)		(0.014)		(0.005)
Log(*A*)	0.072*	0.009*	0.020	–0.052	0.023*	0.024*
	(0.022)	(0.050)	(0.017)	(0.039)	(0.006)	(0.014)
Log(*A*).FD	No	–0.063*	No	–0.072*	No	0.0004
		(0.027)		(0.021)		(0.007)
Log(*S*)	0.175*	0.241*	0.143*	0.225*	0.0003	0.012
	(0.035)	(0.068)	(0.027)	(0.053)	(0.009)	(0.019)
Log(*S*).FD	No	0.066*	No	0.082*	No	0.0003
		(0.032)		(0.025)		(0.009)
$\overline{R}^2$	0.71	0.71	0.77	0.77	0.62	0.62
Chow Test	$H_{0\,;}\ \alpha_1 = \alpha_2 : \beta_1 = \beta_2$ $H_{1\,;}\ \alpha_1 \neq \alpha_2 : \beta_1 \neq \beta_2$		$F - \dfrac{RSS_W - (RSS_1 + RSS_2)/k}{RSS_1 + RSS_2 / n - 2k}$			
	Tabulated values	1% = 2.65 5% = 2.11	Test value	204.13	Result: Reject H_0	

Note: Log (*L*), log (*K*) & log (*F*) represent the log of the unit cost of labor, capital, and funds, while log (*Q*) log (*A*) & log (*S*) represent the log of output, assets, and size respectively. We used 'fixed effects (FE) panel estimation based on the Hausman Test. The financial crises dummy stands 1 in post-GFC and 0 otherwise. The Chow test confirms the structural break in our dataset. ( ) represent standard errors, [ ] show *p*-values. *, **, *** exhibit significance level at 1%, 5% and 10% respectively.

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