Competition, performance and portfolio quality in microfinance markets

A study using global panel data

This version: 02.06.2014

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Abstract

In recent years growing competition in the microfinance industry has been censured for the repayment and other crises . Using the Boone indicator as a measure for competition, our paper investigates the impact of competition on microfinance institutions' (MFIs) outreach, financial performance and quality of loan portfolio. We deal with the potential endogeneity issues by employing the instrumental variable approach using the generalized methods of moments (GMM) estimation technique. Our results show that increased competition in microfinance sector leads to improved depth of outreach and profitability of the sampled MFIs. The data also supports the view that increased competition increases loan portfolio quality.

Keywords: microfinance institutions, competition, outreach, financial performance, capitalization, panel data IV estimation.

JEL Classification:

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1. Introduction

In a competitive setting, by definition, more firms contend for a limited market share. In the financial sector in particular such a setting is vitally important for a number of reasons. First, the degree of competitiveness matters for the productive efficiency of financial services and the quality, diversity and innovativeness of financial products. Second, specific to the financial sector, competition greatly affects the financial stability of an organization (Claessens, 2009). Third, competition significantly affects firms' and households' access to financial services, which, in turn, may impact the consumers' wealth and economic growth and social welfare in general. Particularly in the loan markets, competition may push down loan prices and improve services for consumers and enterprises (Cetorelli, 2001; Bikker et al., 2007; Leuvensteijn et al., 2011; Tabak et al., 2012).

Microfinance institutions (MFIs) are quasi-banks which provide specialized financial services, primarily to poor women, in developing countries. The microfinance industry has experienced a tremendous growth during the last few decades. Subsidized funding from governments, development agencies and commercially oriented funders including commercial banks were the key drivers of growth in microfinance operations (Assefa et al., 2013; Ghosh and Van Tassel, 2011). Such rapid growth has also induced increased competition among the MFIs.

Increased competition impacts the microfinance industry and clients in several ways. First, it weakens the functioning of the dynamic incentive mechanism used by MFIs and leads to higher loan default. Second, increased competition leads to a decline in the borrower quality as better performing clients move to profit-oriented MFIs. Third, interest rates may drop as competition increases, which may lead to a decline in MFIs' profitability and they may not cross-subsidize less-profitable projects (McIntosh and Wydick, 2005). Because of the clustering effect, profit-motivated MFIs enter the markets where pre-existing socially-motivated MFI penetration is high. Profit maximizing MFIs select their clients from the already-trained and screened set of clients of the socially-motivated MFIs, which adversely impacts socially-motivated MFIs' outreach performance. Loan repayment problems coupled with increased competition and information asymmetry may also lead to a decline in portfolio quality (Broecker, 1990); Marquez, 2002) and expose the MFI clients to the risk of over-indebtedness and debt-traps leading to increased sociological and psychological constraints (Schicks and Rosenberg 2011).

The empirical literature on competition in microfinance is scant and this paper attempts to investigate the impact of increased competition in the MFI sector on outreach, financial performance and quality of loan portfolios.

We measure competition using Boone indicator or the ‘profit elasticity’ (PE) indicator. which is based on the Relative Profit Differences (RPD) concept, where competition rewards efficiency (Boone, 2008; Leuvensteijn et al., 2011). The underlying intuition is that in a more competitive market, firms are punished more harshly (in terms of profits) for being inefficient.

We argue later in the paper that other measures of competition like Learner’s index, Panzar-Rosse revenue test, HHI etc. may not assess existing competition scenarios in microfinance appropriately, especially since they are now increasingly being regulated. The PE indicator is robust from both a theoretical and an empirical point of view when compared with more conventional measures of competition like Learner’s index, Panzar-Rosse H-statistic and the Hirfindahl-Hirschman index (Boone et al., 2007).

The paper contributes on several levels. Though Boone indicator has been employed for measuring competition in the banking sector, it has not been used before to estimate competition in the microfinance sector (Schaeck and Cihák, 2010; Boone and Leuvensteijn, 2010; Leuvensteijin et al. 2011). With Boone indicator we move beyond proxying competition with concentration ratios like Herfindahl-Hirschman index (HHI) and Lerner’s index. (Assefa et al. 2013, Baquero et al. 2012). Second, we also deal with the issue of potential endogeneity of MFI performance, competition measure and other covariates using instrumental variables (IV) GMM (generalized method of moments) estimation techniques . Third, the analysis is based on combining three databases. The Microfinance Information Exchange (MIX) database provides information on 521 individual MFIs. For additional information on institutional governance quality, macroeconomic and financial development etc., information from the World Governance Indicators and the World Development Indicatoors have been added.Necessary adjustments have been made to guarantee consistency and comparability between these three data sets.

In subsequent section we discuss the relevant literature (section 2) and various measures of competition (section 3). Section 4 presents the methodology with estimation of our competition measures and econometric specification. The data and the variables are present in section 5 with the discussion of the empirical results in section 6. Finally, Section 7 concludes.

2. Competition in Microfinance

Increased competition amongst the MFIs is the outcome of at least two recent developments in this sector. First, for the last couple of years the industry has grown very rapidly with greater diversification of funding sources and entry of commercial banks and funders that are profit oriented. Second, the number of for-profit commercial microfinance service providers has also increased. These MFIs attempt to achieve financial self-sufficiency while keeping their social mission intact. Arguably balancing the social objectives and financial self-reliance has been challenging for the Microfinance sector.

Increased competition creates problem for the Microfinance sector on several levels. In order to discipline their clients and ensure timely repayments most MFIs use 'dynamic incentives' that links future access to credit with proper repayments of earlier loans. Asymmetric information problems on clients' profiles increase resulting in multiple loans or 'double dipping' by borrowers as increased number of MFIs compete for the same set of clients,. The asymmetric information in the multi-lender market deteriorates the portfolio quality (Broecker, 1990; Marquez, 2002). Moreover, the excessive total debt due to multiple loans, can potentially lead to a further deterioration in the total default rates of MFIs, Thereby rendering the dynamic incentives mechanism dysfunctional (Hoff and Stiglitz, 1998).

Increased competition due to the entry of profit-oriented MFIs induce the profitable clients of the socially-motivated MFIs to shift to the MFIs that lend larger loans and have a higher net returns. This therebyworsens the quality of the portfolio of the socially-motivated MFIs and negatively impacts these MFIs' cross-subsidisation possibilities[3] (Navajas et al., 2003; McIntosh and Wydick, 2005). For the clients increased competition with information asymmetry, leads to the risk of over-indebtedness and debt-traps with increased sociological and psychological constraints (Schicks and Rosenberg, 2011).

Competition also affects the consumers' wealth and the performance and financial soundness of financial service providers (Bikker and Bos, 2005). It has a negative impact on outreach (Assefa et al., 2013) and affects competition affects the product quality, product diversity and productive efficiency of financial institutions (Claessens and Laeven, 2004). Cull et al. (2009a) argue that rising competition leads to market saturation in some countries. Using a concentration index and mainly focusing on depth of outreach Olivares-Polanco (2005), find that increased competition results in lower outreach. While the results remain inconclusive, she argues that the probability of default is higher with increased levels of indebtedness.
Baquero et al. (2012) finds that for-profit MFIs charge significantly lower loan rates and demonstrate better portfolio quality in less concentrated markets. Non-profit MFIs, however, are comparatively insensitive to changes in concentration. Assefa et al. (2013) argue that intense competition is negatively associated with MFI performance as measured by outreach, profitability, efficiency and loan repayment rates. In saturated markets, MFIs try to decrease their costs by lowering lending standards or decreasing screening efforts thus leading to higher loan default rates due to the increase of risky borrowers. Over-aggressive marketing (pressuring borrowers to take new loan after they have just paid off an old one) adds to the risk and may trigger the risk of over-indebtedness. 'Over-confidentiality bias' or a 'hyperbolic discounting', that is, discounting the future too strongly and putting too much weight on the present, can lead borrowers to make bad decisions like taking more debt (Kahnemann and Tversky, 1979). Schicks and Rosenberg (2011) suggest that the use of over-aggressive collection practices and inflexible loan products may cause borrower over-indebtedness. They argue that these problems are aggravated by bad staffs that encourage over-lending, offer wrong products, obscures loan terms and uses of abusive collection practices.

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[3] Cross-subsidisation means reaching out to the unreached wealthier clients in order to finance a larger number of poor clients whose average loan size is relatively small (Kar and Bali Swain (2013).

Hermes et al. (2008) and Cull et al. (2009b) using country-level measures of competition that …, rather than measures reflecting competition at the institutional level.

Hermes et al. (2008) analyse the impact of formal financial development on microfinance efficiency and argue that in a formal financial setting the efficiency of MFIs improves due to competitive pressure. At the same time, cost reductions reduce the outreach of MFIs. In a related paper, Cull et al. (2009b) investigate the performance of MFIs under the pressure of competition from formal banks. Their results show that MFIs faced with high competition tend to reduce the breadth of outreach but focus more on the depth of outreach, i.e. more loans to women borrowers and smaller loans. However, the effect on other performance indicators, such as profitability, appears to be weak.

Inspite of the recent interest in the impact of competition on the financial and social performance of MFIs remains understudied. Most studies remain focussed on performance of MFIs in a few countries. They use a proxy for competition with measures of market concentration which makes comparisons of results difficult.

3. Measures of competition

Estimating the degree of competition in any industry is a challenging task and the banking industry is not an exception. Several methods have been developed for measuring bank competition and they can be broadly divided into two major approaches: the structural, or Industrial Organization (IO) approach and the non-structural, or the new empirical industrial organization (NEIO), approach. The structural method, originates from the industrial organisation theory that tests the market structure to assess the bank competition based on the Structure Conduct Performance (SCP) model. This method uses the number of banks or the degree of banking industry concentration as a proxy for market power. The SCP hypothesis argues that greater concentration causes less competitive conducts and leads to greater profitability of the bank. In this model, competition is measured by concentration indices such as the n-firm concentration ratios or the Herfindahl-Hirschman index Several papers test this model jointly with an alternative explanation of performance, namely the efficiency hypothesis, which attributes differences in performance (or profit) to differences in efficiency (Goldberg and Rai, 1996).

Nevertheless, the structural approach has several deficiencies (Hannan, 1991). Although these hypotheses have frequently been employed in empirical research, they are not always supported by theoretical microeconomic theory (Delis et al., 2008; Claessens and Laeven, 2004; Bikker and Spierdijk, 2008). As a result, the NEIO approach is increasingly being used in recent times to draw inferences on firms' observed behaviour from the estimated parameters derived from theoretical microeconomic models of price and output determination (Lau, 1982; Bresnahan, 1982; Panzar and Rosse, 1987; Carbo et al., 2009). The NEIO approach provides non-structural tests for competition measurement in order to avoid the problems associated with the traditional IO approach. Traditional competition measures suffer from the fact that they infer the degree of competition from indirect proxies such as market structure or market shares. In contrast, non-structural measures do not infer the competitive conduct of the banks through the analysis of market structure, but measure bank conduct directly. Basically, the parameters for the competitive behaviour of firms—such as the price-cost margins—are estimated in the NEIO framework which include the Rosse-Panzar model, which provide an aggregate measure of competition, and the Lerner index, an individual measure of market power.

Within the NEIO framework, there are two main methodologies. One is a simultaneous-equation approach which estimates supply and demand functions to identify a parameter that measures the behaviours of banks. The other is the Panzar and Rosse (1987) model that requires easily available data on firm-specific variables. This model uses a reduced form revenue equation to construct the H-statistic ($-\infty \leq H \leq 1$), calculated as the sum of the elasticities of the total revenues compared to the factor input prices. Intuitively, the H-statistic examines whether a change in factor input prices influences the equilibrium revenues of a bank to measure competition. The value of H-statistic can determine whether there exists perfect competition ($H = 1$), monopoly or perfect collusion ($H = 0$), or monopolistic competition ($1 > H > 0$: any value in between)[4].

Banks' efficiency is frequently used as a proxy for competition. The intuition is that strong competition reduces banks' unused scale economies. Thus, existence of non-exhausted scale economies indicates that there is scope for reducing costs, which indirectly indicates competition, or a lack of it (Bikker and Leuvensteijn, 2008). The X-efficiency literature is focused on the managerial ability to reduce production costs controlling for input prices and outputs (Leuvensteijn et al., 2011). Another view suggests that high profits may indicate a lack of competition. Profitability is commonly measured as a ratio of output price minus the

[4] See Tabak et al. (2012) and Bikker and Spierdijk (2008), for a literature review.

marginal costs (PCM) and the output price. PCM is frequently used to estimate the Lerner index in the empirical IO literature.

4. Methodology

4.1 Measuring competition: The Boone indicator model

In this paper we use the Boone indicator as the measure of competition. The Boone (2008) model considers the impact of efficiency on performance in terms of profits and market shares centring on the idea that more efficient firms (firms with lower marginal costs) gain higher market shares or profits.[5] The higher the degree of competition in the market the stronger this impact is and the more negative the indicator will be. Intuitively it implies that competition improves the performance of efficient firms though it weakens the inefficient firms' performance. The Boone model has several advantages. First, in this model products are assumed close substitutes with no or low entry costs. This is an advantage over the concentration measures and some other competition proxies. Second, using the Boone indicator, it is possible to measure competition for several specific product markets and also different categories of financial institutions. Third, the conventional measures such as the Lerner index and the H–statistics may lead to flawed results especially due to interest rate regulations applicable to most microfinance industries. Fourth, while other measures consider the entire industry, the Boone indicator can measure competition of microfinance market segments, such as the loan market only. Following Schaeck and Cihak (2010), the following model defines the Boone indicator:

$$\ln \pi_{it} = \alpha + \sum_{t=1}^{T} \beta_t \, ln(MC_{it}) + \sum_{t=1}^{T-1} \alpha_t d_t + \mu_{it} \qquad (1)$$

where π_{it} stands for profit of MFI i at year t, MC is the marginal costs of MFI i at year t, β denotes the Boone indicator, d_t is the time dummy and μ_{it} is the time-dependent idiosyncratic error term. The above specification evaluates the competitive conditions for each microfinance sector for each country included in the dataset for the entire period. We add the time dummies to control for temporal evolution of the profits within a country. We expect that MFIs with low marginal costs make higher profits, i.e. $\beta < 0$. Competition tends to increase this effect, since more efficient MFIs outperform less efficient ones. The more negative is β, the higher is the competition level in a market. Positive values for β mean that the more

[5] The Boone (2008) model is founded essentially on the efficiency structure hypothesis of Demsetz (1973).

marginal costs a bank has the more profits it will earn (Leuvensteijin et al., 2011) signifying the presence of extreme level of collusion or competition on quality (Tabak et al., 2012).

The Boone model also provides the yearly estimates of competition to enable examination of the historic evolution of competition. The yearly Boone scores are estimated using the following equation where the individual time dummies are to capture the year-specific factors common to all MFIs in the market:

$$\ln \pi_{it} = \alpha_0 + \sum_{t=1}^{T} \beta_t d_t \, ln(MC_{it}) + \sum_{t=1}^{T-1} \alpha_t d_t + \mu_{it} \qquad (2)$$

We use the return on assets (ROA) as a proxy for profits and following Leuvensteijn et al (2011).[6] The marginal costs (MC_{it}) for each MFI and year in the database is estimated using a separate translog cost function (TCF) as marginal costs are not observed directly[7]. The translog cost function includes one output and three input prices: (price of labour, price of funds and price of capital). The gross loan portfolio is used as a proxy for output. The input prices are proxied by the ratio of personnel expenses to total assets (price of labour), the ratio of financial expenses to total assets (price of funds) and the ratio of administrative expenses to total assets (price of capital). We impose symmetry and linear homogeneity restrictions on the input prices which means that costs increase (decrease) by the same proportion as the increase (decrease) in the input prices. Hence, intuitively, the total costs represent the three inputs included in the cost function. The TCF is specified as follows:

$$\ln TC_{it} = \alpha_0 + \delta_0 \ln q_{it} + \frac{\delta_1}{2} (\ln q_{it})^2 + \sum_{j=1}^{3} \alpha_j \ln W_{jit} + \ln q_i \sum_{j=1}^{3} \alpha_j \ln W_{jit} + \frac{1}{2} \sum_{j,\, k=1}^{3} \alpha_{jk} \ln W_{jit} \ln W_{kit} + \sum_{t=1}^{T-1} \alpha_t d_t + \varepsilon_{it} \qquad (3)$$

where TC_{it} stands for total costs (captured by the total expenditures over assets ratio) of MFI i at year t[8], q_{it} represents output of MFI i at year t captured by the gross loan portfolio, W denotes the three input prices and ε_{it} is an error term. Time dummies (d_t) for each year are also included to capture the technological progress over time.

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[6] The dependent variable is computed as log ($1+ROA_{it}$) to avoid negative values of return on assets in the log specification.
[7] Schaeck and Cihak (2010) approximate a firm's marginal costs by the ratio of average variable costs to total income.
[8] Total costs are the sum of personnel expenses, other non-interest expenses, and interest expenses.

Previous studies (see, for instance, Leuvensteijn et al., 2011) have employed the ordinary least squares (OLS) to estimate the parameters of the cost function. However, employing OLS has several limitations and produces biased parameter estimates resulting from the multicollinearity problem since the TCF includes a large number of explanatory variables. Recently, stochastic frontier (SF) models have become a popular tool for efficiency analysis. Theoretical motivation for the SF model is that no economic agent can exceed the ideal “frontier" and the deviations from this extreme represent the individual inefficiencies. The parametric SF models are a regression model (estimated by likelihood-based methods) with a composite error term that includes the classical idiosyncratic disturbance and a one-sided disturbance which represents inefficiency (Belotti et al., 2012). As an alternative to the SF model data envelopment analysis (DEA) is also sometimes used, which makes general production and distribution assumptions. However, if the assumptions are weak and invalid inefficiency levels may be systematically underestimated in small samples and inconsistency may arise with a bias over the frontier. Thus, this paper uses a parametric SF model to estimate the translog cost function. We use the specification of the TCF (equation 3) in logarithmic form as it allows the interpretation of first-order coefficients as cost elasticities.

The marginal cost of MFI i at year t can then be obtained from the first derivative of equation (3) as follows:

$$MC_{it} = \frac{\partial TC_{it}}{\partial q_{it}} = \frac{TC_{it}}{q_{it}}\left(\delta_0 + \delta_1 \ln q_{it} + \sum_{j=1}^{3} \delta_{j+1} \ln W_{j,it}\right) \qquad (4)$$

Leuvensteijin et al. (2011) and Schaeck and Cihak (2010) suggest potential endogeneity problems (discussed in the next sub-section) in the estimation of equations (1) and (2) as performance and costs are determined simultaneously. To correct for this we employ instrumental variiables with a two-step GMM estimator. we first use the lag of MC_{it} as the instrument., or we choose to use a fixed-effects model (i.e., the within estimator) to estimate the models. The marginal costs are computed by substituting parameter estimates from TCF into equation (4).

4.2 Model Specification

To estimate the effect of competition on the performance indicators of microfinance institutions. The following model is estimated:

$$Y_{ijt} = \alpha' C_{ijt} + \beta' X_{it} + \delta' Z_{jt} + e_t + u_i + \varepsilon_{it} \qquad i = 1,2,\ldots, N;\ t = 1,2,\ldots, T \qquad (5)$$

Where Y_{ijt} represents the performance indicators (proxied by depth of outreach (social performance) and loan portfolio quality of MFI i at time t located in country j). C_{ijt} is a $(1 \times k)$ vector of measures of competition in microfinance that varies over individual MFIs, time and country; X_{it} is a $(1 \times k)$ vector of time-varying observed MFI characteristics that vary over both individual MFIs and time; Z_{jt} is a $(1 \times p)$ vector of macroeconomic and overall governance indicators that varies over both countries and time. All of these variables are assumed to influence outreach, performance and loan portfolio quality (*i.e.*, repayment status) of individual MFIs. The time-specific individual effect e_t is distributed independently across time with variance σ^2_e; u_i is the MFI-specific individual effect and is assumed to be an unobserved time-invariant random variable, distributed independently across MFIs with variance σ^2_u; and ε_{it} is the usual (idiosyncratic) error term, which is assumed to be uncorrelated with the vector columns (C, X, Z, u) and has a zero mean and constant variance σ^2_ε conditional on C_{ijt}, X_{it} and Z_{jt}. Together, $v_{it} = e_t + u_i + \varepsilon_{it}$ is commonly referred to as the composite error term where e_t is the time-varying unobservable time-specific effect, u_i is the time-invariant unobservable individual-specific effect and ε_{it} is the remainder disturbance term.

First, we perform a joint F-test to check poolability following Baltagi (2008), which reveals that both individual and time effects are statistically significant at 1% level. This rejects the homogeneity assumption across MFIs and time and suggests panel data estimations should be employed. However, an additional difficulty in estimating the model is that measures of MFI (financial performance, depth of outreach and loan portfolio quality) can be simultaneously determined by unobservable managerial competence or aptitude. Endogeneity may arise due to other reasons too. For example, financial self-sufficiency (FSS) and return on assets (ROA) are the common measures of financial performance of MFIs. These ratios are determined by financial revenue which consists of interest rate and fees components. For instance, FSS is determined by the ratio of financial revenue to the sum of financial expense, loan loss provision expense and operating expense. Covariates like portfolio yield, which is the proxy for interest rates is also defined as a ratio of interest (and fees) on loan portfolio and gross loan portfolio. The endogeneity comes from the uncontrolled confounding variable—interest and fees—as it is an extraneous variable which correlates with both the dependent and the independent variable. Again, for the relation between loan portfolio quality and portfolio yield, reverse causality (another source of endogeneity) is at work, since it is unclear whether loan delinquency rates are affected by portfolio yield or vice versa.

Endogeneity weighs down the estimates with inconsistency and inefficiency. We employ the instrumental variables (IV) estimations to deal with this. Baltagi (2008) suggests that IV estimations can take care of the potential problems associated with outliers with bad leverage and weak instruments in unbalanced panel data. We employ one- and two-step GMM estimators since they are robust to violations of homoscedasticity and normality. Since we have large N and small T panels, the GMM estimator takes care of arbitrary heteroskedasticity and serial dependence problems using the optimal weighting matrix (Wooldridge 2002). The endogeneity bias is overcome finding a set of relevant instruments independent of the error term. We need at least as many instruments (L) as regressors (K). So, the lagged explanatory variables have been used as the instruments. Since $L > K$, we have a set of over-identifying restrictions. The instruments' independence from the error term is then tested with Hansen's (1982) J-test which is distributed as chi^2 with (L – K) degrees of freedom. A high value of chi^2 (and very low p-value) indicates that some of the instruments are still correlated with the error term, and therefore, the endogeneity problem persists.

As the analysis in this paper uses MFI-specific and country-level yearly data, MFI-level fixed effects (FE) are most likely to capture the differences in individual data, and therefore, estimations through the fixed effects (FE) models of (5) are quite justified. We include FE and time effects to capture MFI-specific and time-specific effects. To test the robustness of the results fixed-effects 2SLS (FE2SLS), error components 2SLS (EC2SLS) and LIML (limited information maximum likelihood) estimations were also performed and the results remained largely unperturbed.

5. Data and variables

The analysis in this paper is based on the MFI-level data that were obtained from individual MFI profiles that voluntarily reported to the Microfinance Information Exchange (MIX) database[9]. So far, this is the most detailed and publically available data on financial, portfolio and outreach performance of MFIs. MIX collects data from many sources including audits, internal financial statements and management reports of respective MFIs. To ensure accuracy,

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[9] Individual MFI data are maintained in their publicly available information platform: www.mixmarket.org.

they review and validate the data against about 135 quality checks and 150 data audit rules. Besides, MIX uses ‘diamonds’ to rank the MFI-data quality on a scale of 1 to 5, where 5-diamonds imply the best quality[10]. Country-level data on institutional governance quality and macroeconomic and financial development were collected from the WGI (Worldwide Governance Indicators) and WDI (World Development Indicators) databases of the World Bank. Initially, we have data from 1144 MFIs which have been currently in operation in 35 countries from 1996 to 2010 (7146 observations). In the final dataset we kept MFIs with at least a level-3 disclosure rating to ensure that only high-quality data have been included. However, to avoid any potential bias in sample selection we also included 28 observations on MFIs which have less than level 3-diamonds disclosure rating[11]. Combining data from three different sources results in loss of observations as information on several micro- and macro-variables were not available for all MFIs and countries. Besides, due to missing values with variables we had to drop many MFIs from the initial dataset. Additionally, as we use two time lags in several estimations, our database reduces to 3001 observations for 2003 to 2010. Our resulting sample for estimating the Boone indicator is thus an unbalanced panel[12] of 521 MFIs from 10 countries (Bangladesh, India, Nepal, Indonesia, Philippines, Bolivia, Ecuador, Mexico, Nicaragua and Peru), totalling 3001 observations. Then, ten separate panel datasets have been created corresponding to the microfinance sectors in each of these countries.
Table 1 provides number of observations by country and year and Table 2 provides number of observations by country and MFI legal types.

This allows us to investigate the regional differences (between South Asia, East Asia and the Pacific and Latin America and the Caribbean) in the level of competition. These countries have differences in their regulatory frameworks and revenue streams. But when we employ the Boone indicator to measure competition, differences in country-specific revenue sources do not matter much. Thus we can compare the revenue stream of a ‘micro-saving’ centric country (Indonesia), for instance, with that of a ‘microloan’ centric country (India). Second, in this study countries where the microfinance sectors are getting increasingly competitive and are characterized by differing levels of concentration have been chosen. Third, these countries are of varying magnitudes of population, GDP and footprint of the microfinance sectors. For

[10] However, the for performance analysis we need to adjust the data for subsidies and grants, which we could not accomplish due to data limitations. But many studies have used these unadjusted data for their analysis though. For details see: http://www.mixmarket.org/about/faqs#ixzz31U4uX8pM
[11] This study sampled MFIs which have: 5-diamonds (20.96%), 4-diamonds (42.09%), 3-diamonds (36.02%) less than 3-diamonds (0.93%).
[12] Some MFIs report information for a minimum of 3 years while others report for 4-8 years.

example, India is one of the largest countries in the world, with a population of around 1.27 billion in 2013, Ecuador and Peru have much smaller populations (15.4 million and 30.4 million respectively).

MFIs usually have two broad objectives—social and financial. Financial performance of an MFI is usually measured by indicators—FSS (financial self-sufficiency) and ROA (return on assets)—whereas the depth of outreach measures their social performance. Average loan size (adjusted by GNI per capita) and percentage of female borrowers are two common indicators of MFIs' depth of outreach. FSS, a measure of MFI-profitability and self-sustainability, accounts for the MFIs' ability to generate sufficient financial and operating revenues to cover costs. ROA, however, measures how well the MFI uses its total assets to generate returns. This paper employed FSS and ROA as proxies for MFI performance. In order to measure MFIs’ loan repayment performance, portfolios-at-risk past 30 days (PAR30)—the standard measure of MFIs’ loan portfolio quality—is also used. PAR ratio is calculated by dividing the PAR by the gross loan portfolio. Larger PAR values indicate increased loan risk, or lower repayment performance. The explanatory variables include competition (as estimated by Boone indicator), MFI characterises (real portfolio yield, focus on lending, age, size and several country-specific macroeconomic indicators to control for overall macroeconomic environment (inflation rate, growth in GDP per capita, rural population growth, spread and domestic credit.

Table A1 in the appendix presents the means and standard deviations of the country-environment variables that we employ in the competition-performance models. Economic and financial sector development indicators and overall governance indicators have been included in our models which we use to control for cross-country differences in these conditions. As one can clearly note from this table, there are wide variations in terms of economic development and overall governance among the selected countries. Some economies are dynamic with satisfactory social conditions while others are more vulnerable and present poor social indicators. Together these may have a direct influence on the profitability and social performance of the corresponding microfinance markets.

Following Ahlin et al. (2011) and Cull et al. (2009a), we also included several governance indicators—control of corruption, political stability, rule of law and regulatory quality—in order to control for the quality of institutions. Table 3 provides the variable definitions and Table 4 provides the summary statistics of the dependent and explanatory variables used in the regression analyses. MFIs are of varying age, ranging from very new (age = 0) to extremely matured (age = 61). In terms of focus on lending, MFIs in the sample are of diversified categories, ranging from no lending to lending of about 25% of their total assets. MFIs' size reflects a widely dispersed distribution as well.

6. Discussion on empirical results

6.1 Boone coefficient scores

Table 5 presents the mean and standard deviations of the MFI-level input price and output variables used in the translog cost specification by country. Evidently, MFIs from Bangladesh, Bolivia, Mexico and Peru generally have the largest loan portfolios. The Boone scores in Table 6 confirm that the included MFIs are highly competitive (negative Boone-scores) whereas on average MFIs in Mexico and Indonesia show greater collusion(positive Boone scores). Table 8 shows the cross-correlation between our main independent variables of the model, as well as the corresponding significance levels.

Table 7 presents the historical evolution of the Boone scores by country for the whole period (2003-10). In recent years markets in Bangladesh and Nicaragua have shown a statistically significant competition . India (2009) and Peru (2010) also show significant competition that corresponds to years of crisis in the microfinance industry, especially in India. Ecuador on the other hand seems to have moved away from competition. Bolivia and Indonesia on the other hand show a tendency to collude in certain years.

7.2 Competition and MFI-performance analysis

The results for the effect of competition on performance outcome in terms of outreach, financial performance and loan portfolio quality of MFIs, are presented in Tables 9-11. A number of country-level variables have also been utilized in estimations in order to control for overall macroeconomic environment and institutional quality. At the outset diagnostic tests were run to check for potential problems of joint determination of performance, measure of competition, portfolio yield and size. We confirm such problem based on the endogeneity tests and consequently employ instrumental variables (IV) regression methods with two-step generalized method of moments (GMM) technique. While estimating our model using the first- and second-lagged values of the explanatory variables as the instruments. Kernel-based heteroskedasticity and autocorrelation (HAC) adjusted standard errors have been used in estimations. The instruments' independence of the error term is then tested with Hansen's

(1982) J-test. High p-values of the J-tests confirm the econometric validity of the instruments used in the analysis. The estimates are presented in three specifications—estimations without macroeconomic and governance indicators, estimations with only the macroeconomic indicators and finally those with the governance indicators.

In Table 9, we measure MFIs' depth of outreach with the average loan size adjusted by GNI per capita and percentage of female borrowers. As mentioned before, higher negative values of the Boone indicator indicates more competitiveness. Results in Table 9 shows that the coefficients of the Boone indicator variable in columns 1-3 are negative, but statistically insignificant However, the results in terms of average loan size (adjusted) are negative and highly significant except model 3 (columns 4 and 5). A negative Boone indicator implies higher levels of competition average loan size decreases. This may be interpreted to supportive of the hypothesis that MFIs in these 10 countries are still able to maintain their lending operations to the relatively poor as depth of outreach increases (decrease in average loan) in spite of increased competition. Depth of outreach also increases with increase in real yield. The coefficients for the size variable are always positive and significant in model 2 of female borrowers' regressions. Size coefficients are highly significant in average loan size regressions. Together these results suggest that with increased MFI size (in terms of total assets) female participation improves (increase in depth of outreach), but average loan size increases with such improvement. So, evidently MFIs continue to maintain their focus on women as the major clients, but loan size over the years have risen too, meaning that comparatively less poor women are now getting loans or possibly women are in a better position to afford bigger loans. Interesting results are found in terms of the institutional quality variables. Results show that with better regulatory quality and control of corruption measures women are getting fewer loans while improved rule of law ensures higher women participation. On the contrary better control of corruption is linked with higher average loan size. Other variables do not seem to have any significant link with the depth of outreach measures.

Table 10 presents the results for the financial performance of MFIs in terms of FSS and ROA. Our results show that as the Boone indicator becomes more positive (collusiveness), i.e., competition decreases and MFIs' self-sufficiency and profitability increases. So, as expected, increased competition in microfinance is compatible with higher financial self-sufficiency. One plausible explanation for this result might be the fact that competition among the MFIs in the sampled countries has not yet reached the level where with increased market power profit margins have declined enough to encourage MFIs to provide risky loans. This seems plausible as we see that as a result of increased market power MFIs are still able to maintain cautious lending operations through smaller loans. It may therefore be possible for them to earn some returns to become self-sufficient. As the results show, quite logically, an increase in real portfolio yields helps to improve MFIs' self-sustainability. The trend is similar for their focus on lending: more lending out total assets just helps improving financial performance. MFI-size variable is always positive and highly significant meaning that bigger MFIs perform better financially and hence, become self-reliant. The coefficient of the age variable is always positive, but rarely significant statistically. This suggests that as MFIs age they perform well financially. The coefficients of the regulatory quality variable are negative and highly significant. This is suggestive of the fact that quality of regulation is now very important and with its better functionality the sampled MFIs may not achieve higher financial performance. Again, an improved state of rule of law just helps in ensuring MFIs' better financial performance.

Table 11 shows the results of the link between competition and quality of loan portfolio. In the analysis, we use two measures of nonperforming loans (NPLs) in terms of gross loan portfolio as the proxies for loan portfolio risk: Portfolios–at-risk past 30 days (PAR30) and portfolios–at-risk past 90 days (PAR90). The Boone indicator coefficients are always negative and highly significant except in two models. So, the findings indicate that as the Boone indicator becomes more negative (increased competition) MFIs' are confronted with less risky loan portfolios. MFIs' high default means low loan portfolio quality and increased competition may lead to dual or multiple borrowing resulting in heavy debt burden and low repayments. However, MFIs in this sample have been able to cautious lending operations and quality of their loan clients to maintain better repayments. This may happen for other reasons as well. First, loan repayments may increase as borrowers can repay borrowing from other lenders. This creates a debt trap, which is a worrying issue in recent times. Second, MFIs in competitive environments become more professional and apply improved, comprehensive and thought-through collection strategies. Finally, commercial lenders are aggressive collectors who do not allow loan defaults especially in this dataset, which is dominated by commercial lenders from the Latin America region. Perhaps the situation would be different for MFIs from the Asia, Africa or East Europe which are more socially motivated if regional perspectives are considered. Finally, among the control variables, we find that for older MFIs repayment performance is better and such performance has an increasing trend (as the coefficients of the age^2 variables are positive significant at least in two models). However, MFI-size does not matter much for NPLs. Therefore, it may not be the case that Bigger MFIs have a better loan portfolio quality or better monitoring capability than smaller ones. We also find that as rural population grows NPLs also grow. One plausible explanation for this is that with increased rural population, MFIs may not apply better screening and cautious lending methods. As a result, NPLs increase.

7. Conclusions

This paper aims at determining whether competition impacts on MFIs' depth of outreach, financial performance and quality of loan portfolio for 521 MFIs 10 selected countries with high and vibrant presence of microfinance activities between 2003 and 2010. Only a handful of previous studies have explored these issues. Among them, for instance, Assefa et al. (2013) have used the Lerner's index as a measure of competition without taking into consideration of endogeneity of performance and competition. This paper differs in that we take care of such endogeneity issues and employ a new and relatively advanced technique of competition measurement, the Boone indicator of the microfinance loans markets which characterizes the effects of the earning market share of more efficient MFIs. Application of this technique is quite in the microfinance literature. We first estimate this indicator from translog cost function through stochastic frontier analysis and then regress this indicator on MFI performance and loan portfolio quality measures to check whether varying levels of competition affect them. Using MIX Market data and employing GMM estimation technique our results suggest that competition among MFIs is actually not bad as it improves their performance (social and financial) and loan portfolio quality. Although social performance is improved in terms of average loan size, but the effect of competition on female participation is statistically insignificant.

Thus we see that competition in microfinance did not bring much of the negative effects. However, negative effects of increased competition, if any, can be minimized, for example, through improved regulatory measures. This way competition can be safeguarded while loan portfolio quality is maintained. As previous studies suggest, sharing information among the MFIs can potentially contribute to lower delinquency rates as well as prevent borrowers from taking multiple loans and getting into debt traps. However, our results need to be qualified by the limitation that we did not take subsidies, donations and grants take into account while calculating the MFIs' real return on assets. Moreover, the MIX data is biased towards self-sufficient and commercially oriented MFIs and dominated by Latin American MFIs. In addition to the above data limitations, future research should specifically attempt to focus on using alternative measures of competition and how competition affects efficiency, screening and monitoring scenarios of MFIs operations.

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Table 1: Number of observations by country and year

Country/Year	2003	2004	2005	2006	2007	2008	2009	2010	Total
Bangladesh	43	53	54	36	32	29	28	27	302
Bolivia	11	18	20	25	24	23	23	23	167
Ecuador	24	19	35	43	46	47	43	40	297
India	31	67	73	79	68	80	78	71	547
Indonesia	21	23	25	40	40	31	18	16	214
Mexico	5	8	26	33	45	41	39	39	236
Nepal	15	22	26	33	33	32	28	27	216
Nicaragua	19	24	25	24	25	26	25	23	191
Peru	31	42	45	50	58	60	58	57	401
Philippines	36	55	60	61	61	61	57	39	430
Total	236	331	389	424	432	430	397	362	3001

Table 2: Number of observations by country and MFI legal types

Country name	Legal type						
	NGO	NBFI	Bank	RB	CU-Coop	Others	Observations
Bangladesh	289	0	8	0	5	0	302
Bolivia	93	38	24	0	12	0	167
Ecuador	101	0	32	0	164	0	297
India	259	223	6	8	40	11	547
Indonesia	25	0	0	165	17	7	214
Mexico	35	178	12	0	11	0	236
Nepal	63	42	19	44	48	0	216
Nicaragua	140	14	14	0	23	0	191
Peru	124	218	8	0	51	0	401
Philippines	177	0	13	234	6	0	430
Observations	1306	713	136	451	377	18	3001

1=NGO, 2=NBFI, 3=Bank, 4=Rural Bank, 5=CUCOOP, 6=Other

Table 3: Variable descriptions

Variable name	Definition	Source
Dependent variables		
Average loan balance adjusted by GNI per capita	Average loan balance per borrower/GNI per capita	MIX Market
Female borrowers	Percentage of female borrowers	MIX Market
Financial self-sufficiency (FSS)	Financial revenue/(Financial expense + Loan loss provision expense + Operating expense)	MIX Market
Return on assets (adjusted) (ROA)	Adjusted net operating income after taxes/Average total assets	MIX Market
Portfolio-at-risk past 30 days (PAR30)	Portfolio-at-risk past 30 days / Gross loan portfolio	MIX Market
Explanatory variables		
Boone indicator	A proxy for competition; Explanatory variable of specifications (1) and (2). The absolute value of the β_t in equation (2).	The authors
Real yield on gross loan portfolio	[Yield on gross portfolio (nominal) – Inflation rate] / (1 + Inflation rate)	MIX Market
Size	The natural logarithm of total assets (Total net asset accounts) in US$	MIX Market
Age	Number of years in microfinance operation	MIX Market
Age-squared	Squared value of the age variable	The authors
Focus on lending	Gross loan portfolio / Total assets	MIX Market
Inflation	Rate of inflation, GDP deflator	WDI
GDP growth	Growth of real GDP per capita	WDI
Rural population growth	Percent of rural population growth	WDI
Domestic credit	Domestic credit provided by the banking sector (% of GDP)	WDI
Spread	Interest rate spread (lending rate minus deposit rate, %)	WDI
Control of corruption	Aggregate governance indicator of ‘control of corruption’	WGI
Political stability	Aggregate governance indicator of ‘political stability’	WGI
Regulatory quality	Aggregate governance indicator of ‘regulatory quality’	WGI
Rule of law	Aggregate governance indicator of ‘rule of law’	WGI

Table 4: Summary statistics of dependent variables used in the regression analyses

Variable	N	Mean	SD	Min	Max
Dependent variables					
Female borrower	2435	0.754	0.264	0	1.272
Average loan (adj.)	2904	0.409	0.672	0	9.975
FSS	2099	0.924	0.274	-0.470	4.906
ROA	2533	0.021	0.075	-1.013	0.563
PAR30	2628	0.067	0.105	0	1
PAR90	2137	0.051	0.091	0	0.995
Explanatory variables					
Boone indicator	3001	-0.010	0.023	-0.091	0.109
Real yield	2032	0.255	0.183	-0.106	1.193
Loan-to-assets ratio	3000	0.773	0.519	0	24.941
Size	3001	15.545	1.938	0	21.254
Age	2984	15.341	10.861	0	61
Growth of GDP p.c.	3001	3.967	2.759	-5.891	9.126
Inflation	3001	0.064	0.033	-0.024	0.181
R. population growth	3001	0.527	0.679	-0.519	2.002
Domestic credit	3001	45.059	17.375	14.415	71.842
Spread	2324	8.504	5.459	3.902	22.944
Control of corruption	3001	-0.615	0.308	-1.488	-0.100
Political stability	3001	-1.143	0.456	-2.121	-0.094
Regulatory quality	3001	-0.349	0.455	-1.279	0.461
Rule of law	3001	-0.591	0.371	-1.252	0.185

Table 5: Mean and standard deviations of output and prices of inputs employed in the translog cost function

Country	GLP	AEA	FEA	PEA
Bangladesh	4.36e+07	0.038	0.038	0.089
	(1.32e+08)	(0.033)	(0.021)	(0.027)
Bolivia	5.48e+07	0.056	0.043	0.074
	(9.22e+07)	(0.029)	(0.018)	(0.034)
Ecuador	1.99e+07	0.066	0.042	0.074
	(4.68e+07)	(0.051)	(0.022)	(0.052)
India	2.66e+07	0.050	0.077	0.060
	(9.29e+07)	(0.060)	(0.031)	(0.051)
Indonesia	6264720	0.054	0.082	0.076
	(3.89e+07)	(0.044)	(0.038)	(0.063)
Mexico	6.00e+07	0.151	0.064	0.208
	(1.91e+08)	(0.076)	(0.038)	(0.119)
Nepal	2736937	0.025	0.054	0.051
	(3527610)	(0.023)	(0.015)	(0.027)
Nicaragua	1.45e+07	0.090	0.063	0.097
	(2.57e+07)	(0.053)	(0.033)	(0.051)
Peru	6.14e+07	0.075	0.061	0.099
	(1.33e+08)	(0.040)	(0.026)	(0.067)
Philippines	6770964	0.095	0.043	0.120
	(9618705)	(0.044)	(0.018)	(0.083)

Note: Standard deviations are in the parentheses.

Table 6: Summary statistics of the Boone indicator for various countries (2003-10)

Country	Mean	Median	SD	Minimum	Maximum	N
Bangladesh	-0.033	-0.031	0.015	-0.059	-0.011	302
Bolivia	-0.008	0.001	0.021	-0.050	0.020	167
Ecuador	-0.008	-0.001	0.013	-0.038	0.006	297
India	-0.011	-0.009	0.031	-0.058	0.035	547
Indonesia	0.003	0.005	0.012	-0.019	0.017	214
Mexico	0.002	-0.0004	0.028	-0.035	0.109	236
Nepal	-0.008	-0.007	0.005	-0.016	-0.0004	216
Nicaragua	-0.025	-0.026	0.038	-0.091	0.018	191
Peru	-0.006	-0.012	0.012	-0.018	0.024	401
Philippines	-0.008	-0.009	0.005	-0.014	0.001	430
Total	-0.010	-0.010	0.023	-0.091	0.109	3001

Table 7: Developments of the Boone scores over time for various countries

Year/Countries	Bangladesh		India		Nepal		Indonesia	
	Boone	t	Boone	t	Boone	t	Boone	t
2003	-0.059	-1.29	-0.004	-0.02	-0.014	-0.70	-0.012	-0.73
2004	-0.042	-1.01	0.035	0.27	-0.010	-0.43	0.004	0.14
2005	-0.041	-1.63	-0.009	-0.20	-0.016	-0.42	0.006	0.32
2006	-0.036	-0.75	0.012	0.34	-0.000	-0.02	0.005	0.51
2007	-0.031	-1.14	0.015	0.49	-0.007	-0.57	0.017*	2.03
2008	-0.031**	-3.02	-0.013	-0.48	-0.007	-0.69	0.015	1.30
2009	-0.013**	-2.76	-0.053*	-2.07	-0.008	-0.84	-0.015	-1.18
2010	-0.011**	-3.15	-0.058	-1.97	-0.004	-0.39	-0.019	-1.17

Year/Countries	Philippines		Bolivia		Ecuador		Mexico	
Boone	t	Boone	t	Boone	t	Boone	t	
2003	-0.013	-1.06	-.050	-0.89	-0.000	-0.01	-0.035	-0.37
2004	0.001	0.14	0.001	0.05	-0.038**	-2.92	0.109	0.42
2005	-0.008	-1.44	-0.024	-1.80	-0.009	-1.16	0.039	0.53
2006	-0.009	-1.48	-0.028	-1.73	-0.024**	-2.99	-0.022	-0.66
2007	-0.010	-1.85	-0.022	-1.29	-0.014	-1.45	0.013	0.36
2008	-0.002	-0.32	0.011	0.77	0.005	0.53	-0.000	-0.01
2009	-0.011	-1.72	0.010	0.77	0.006	0.52	-0.018	-0.62
2010	-0.014	-1.68	0.020*	2.20	-0.001	-0.04	-0.011	-0.39

Year/Countries	Nicaragua		Peru	
	Boone	t	Boone	t
2003	0.018	0.39	0.006	0.37
2004	0.010	0.27	0.024*	2.28
2005	-0.034	-0.60	-0.010	-1.38
2006	-0.026	-0.57	-0.012	-1.80
2007	0.007	0.21	-0.012	-1.69
2008	0.000	0.03	-0.013	-1.64
2009	-0.079**	-2.84	-0.003	-0.55
2010	-0.091***	-3.73	-0.018*	-2.49

Table 8: Correlation coefficient matrix of explanatory variables

	Boone	RY	L/A	Size	Age	GDP	INF	RP	DC	SP	CC	PS	REG	Rule
Boone	1.000													
RY	0.132*	1.000												
L/A	-0.009	-0.142*	1.000											
Size	-0.142*	-0.109*	-0.051*	1.000										
Age	-0.093*	-0.182*	-0.038*	0.233*	1.000									
GDP	-0.039*	-0.217*	0.030	-0.009	-0.044*	1.000								
INF	0.074*	-0.284*	0.025	-0.107*	-0.096*	0.041*	1.000							
RP	-0.114*	-0.115*	-0.032	-0.195*	0.129*	0.059*	-0.056*	1.000						
DC	-0.218*	-0.291*	0.021	-0.087*	-0.041*	0.175*	0.207*	0.680*	1.000					
SP	0.0301	0.004	0.1774*	0.2288*	-0.0148	0.3504*	-0.311*	-0.615*	-0.647*	1.000				
CC	0.315*	0.293*	0.025	0.010*	-0.218*	0.148*	-0.096*	-0.256*	-0.197*	0.453*	1.0000			
PS	0.073*	0.119*	0.054*	0.2049*	-0.134*	-0.131*	0.048*	-0.508*	-0.290*	0.288*	0.351*	1.000		
REG	0.181*	0.500*	-0.025	0.109*	-0.083*	0.090*	-0.284*	-0.139*	-0.232*	0.406*	0.734*	0.124*	1.000	
Rule	0.090*	-0.014	0.044*	-0.093*	-0.193*	0.437*	-0.087*	0.396*	0.466*	-0.084*	0.487*	-0.122*	0.423*	1.000

Table 9: Table: Effect of competition on depth of outreach by country-specific microfinance industries

	Percent of female borrowers			Average loan (adjusted)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Boone indicator	-0.711	-0.441	-0.232	-1.447*	-1.969***	0.346
	(0.550)	(0.340)	(0.180)	(0.597)	(0.509)	(0.441)
Real yield	-0.845	-0.809	0.233	-0.498**	-0.527**	-0.242
	(0.697)	(0.655)	(0.228)	(0.171)	(0.172)	(0.244)
Log of loans/assets ratio	-0.029	-0.024	-0.022	0.016	-0.011	0.001
	(0.046)	(0.043)	(0.026)	(0.428)	(0.450)	(0.899)
Size	0.092*	0.085	0.033*	0.174***	0.179***	0.068*
	(0.047)	(0.046)	(0.016)	(0.045)	(0.046)	(0.032)
Log of age	-1.120	-1.114	-0.365	-0.372	-0.386	-0.140
	(0.597)	(0.694)	(0.216)	(0.237)	(0.236)	(0.162)
Age-squared	0.348	0.351	0.123	0.143	0.148	0.075
	(0.200)	(0.233)	(0.086)	(0.089)	(0.088)	(0.072)
Growth of GDP per capita	0.002	0.004		-0.002	-0.003	
	(0.004)	(0.003)		(0.006)	(0.005)	
Inflation	-0.250	-0.244		-0.357	-0.106	
	(0.233)	(0.192)		(0.349)	(0.291)	
Rural population growth	-0.111	-0.087		-0.106	-0.148	
	(0.161)	(0.145)		(0.177)	(0.171)	
Domestic Credit	-0.001	-0.001		-0.006*	-0.006*	
	(0.001)	(0.002)		(0.002)	(0.003)	
Interest Rate Spread	0.001	0.004		0.005	0.002	
	(0.006)	(0.006)		(0.010)	(0.007)	
Control of Corruption	0.025		-0.088*	0.117		0.184*
	(0.098)		(0.045)	(0.096)		(0.081)
Political Stability	0.021		0.016	-0.022		-0.028
	(0.040)		(0.027)	(0.065)		(0.051)
Regulatory Quality	0.002		-0.175*	-0.159		0.089
	(0.158)		(0.081)	(0.101)		(0.091)
Rule of Law	-0.101		0.169*	0.179		0.207
	(0.185)		(0.066)	(0.113)		(0.109)
Hansen J-statistic	0.716	0.766	4.872	0.003	0.003	0.115
P-value	0.8693	0.8575	0.1814	0.9564	0.9552	0.7348
Observations (Groups)	616 (184)	616 (184)	858 (252)	1124 (280)	1124 (280)	1488 (366)

Note: Time effects were included. * p<0.05, ** p<0.01, *** p<0.001

Table 10: Effect of competition on financial sustainability by country-specific microfinance industries

	Financial self-sufficiency			Return on assets		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Boone Indicator	0.976*	0.962**	0.161	0.436**	0.436	0.343*
	(0.431)	(0.355)	(0.292)	(0.147)	(0.268)	(0.152)
Real yield	0.308**	0.247*	0.421**	0.125**	-0.659	0.345
	(0.103)	(0.097)	(0.135)	(0.048)	(0.470)	(0.279)
Log of loans/assets ratio	0.473*	0.439	0.659	0.254*	-0.353	0.022
	(0.237)	(0.227)	(0.425)	(0.104)	(0.305)	(0.020)
Size	0.099**	0.097**	0.108***	0.045**	0.022	0.032*
	(0.032)	(0.033)	(0.021)	(0.016)	(0.042)	(0.013)
Log of age	0.329	0.348	0.280*	0.065	0.271	0.111
	(0.178)	(0.183)	(0.129)	(0.106)	(0.266)	(0.058)
Age-squared	-0.172*	-0.161*	-0.133*	-0.047	-0.089	-0.044*
	(0.070)	(0.071)	(0.055)	(0.037)	(0.090)	(0.022)
Growth of GDP per capita	0.007	0.007*		0.003	0.000	
	(0.004)	(0.003)		(0.002)	(0.003)	
Inflation	-0.308	-0.219		-0.039	-0.183	
	(0.215)	(0.175)		(0.056)	(0.158)	
Rural Population Growth	0.113	0.054		0.015	-0.159	
	(0.119)	(0.099)		(0.035)	(0.127)	
Domestic Credit	0.002	0.003		0.000	0.001	
	(0.002)	(0.002)		(0.001)	(0.001)	
Interest Rate Spread	-0.005	-0.000		-0.001	-0.001	
	(0.006)	(0.005)		(0.002)	(0.004)	
Control of Corruption	-0.029		-0.145*	-0.007		-0.037
	(0.074)		(0.060)	(0.019)		(0.026)
Political Stability	-0.002		0.036	0.002		0.006
	(0.048)		(0.034)	(0.014)		(0.018)
Regulatory Quality	-0.250***		-0.222***	-0.062**		-0.117*
	(0.068)		(0.062)	(0.024)		(0.055)
Rule of Law	0.129		0.173*	0.077**		0.061
	(0.084)		(0.076)	(0.028)		(0.048)
Hansen’s J-statistic	1.006	1.161	5.651	3.650	1.260	0.797
P-value	0.3157	0.2813	0.0175	0.0561	0.5327	0.3720
Observations	1139 (282)	1139 (282)	1507 (369)	1142 (283)	751 (211)	1004 (280)

Note: Time effects were included. * p<0.05, ** p<0.01, *** p<0.001

Table 11: Effect of competition on loan portfolio quality by country-specific microfinance industries

	PAR30			PAR90		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Boone Indicator	-0.449	-0.740**	-0.799***	-0.416	-0.714**	-0.764***
	(0.323)	(0.257)	(0.203)	(0.275)	(0.223)	(0.186)
Real yield	0.436	0.393	0.036	0.258	0.261	-0.011
	(0.345)	(0.327)	(0.243)	(0.305)	(0.288)	(0.224)
Log of loans/assets ratio	0.067	0.065	0.017	0.075	0.073	0.027
	(0.045)	(0.045)	(0.038)	(0.040)	(0.041)	(0.035)
Size	0.015	0.024	0.010	0.017	0.024	0.005
	(0.029)	(0.029)	(0.017)	(0.026)	(0.027)	(0.016)
Log of age	0.248	0.257	-0.196**	0.112	0.125	-0.184**
	(0.273)	(0.300)	(0.066)	(0.226)	(0.254)	(0.063)
Age-squared	-0.075	-0.079	0.080*	-0.024	-0.030	0.080**
	(0.088)	(0.094)	(0.032)	(0.071)	(0.078)	(0.030)
Growth of GDP per capita	-0.000	-0.002		0.000	-0.002	
	(0.003)	(0.002)		(0.002)	(0.002)	
Inflation	0.098	0.069		0.010	0.021	
	(0.159)	(0.136)		(0.139)	(0.118)	
Rural Population Growth	0.294***	0.277**		0.237**	0.217**	
	(0.087)	(0.087)		(0.072)	(0.073)	
Domestic Credit	-0.000	0.000		-0.001	-0.000	
	(0.001)	(0.001)		(0.001)	(0.001)	
Interest Rate Spread	0.007*	0.003		0.008**	0.004	
	(0.003)	(0.003)		(0.003)	(0.003)	
Control of Corruption	-0.047		-0.024	-0.017		-0.015
	(0.065)		(0.043)	(0.058)		(0.038)
Political Stability	-0.016		0.002	-0.028		-0.008
	(0.035)		(0.026)	(0.029)		(0.024)
Regulatory Quality	-0.033		0.004	-0.015		0.005
	(0.064)		(0.052)	(0.058)		(0.048)
Rule of Law	0.156		0.025	0.108		0.002
	(0.082)		(0.055)	(0.072)		(0.050)
Hansen’s J-statistic	2.379	2.280	6.336	2.810	2.887	4.591
P-value	0.3043	0.3198	0.0421	0.2453	0.2361	0.1007
Observations (Groups)	734 (207)	734 (207)	981 (275)	736 (208)	736 (208)	983 (276)

Note: Time effects were included. * p<0.05, ** p<0.01, *** p<0.001