

Kar, Ashim Kumar; Swain, Ranjula Bali

Working Paper

Competition, performance and portfolio quality in microfinance markets

Working Paper, No. 2014:8

Provided in Cooperation with:

Department of Economics, Uppsala University

Suggested Citation: Kar, Ashim Kumar; Swain, Ranjula Bali (2014) : Competition, performance and portfolio quality in microfinance markets, Working Paper, No. 2014:8, Uppsala University, Department of Economics, Uppsala,
<https://nbn-resolving.de/urn:nbn:se:uu:diva-235539>

This Version is available at:

<https://hdl.handle.net/10419/123797>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



UPPSALA
UNIVERSITET

Department of Economics

Working Paper 2014:8

*Competition, performance and portfolio
quality in microfinance markets*

Ashim Kumar Kar and Ranjula Bali Swain

Department of Economics
Uppsala University
P.O. Box 513
SE-751 20 Uppsala
Sweden
Fax: +46 18 471 14 78

Working paper 2014:8
November 2014
ISSN 1653-6975

COMPETITION, PERFORMANCE AND PORTFOLIO QUALITY IN MICROFINANCE MARKETS

ASHIM KUMAR KAR AND RANJULA BALI SWAIN

Competition, performance and portfolio quality in microfinance markets

Ashim Kumar Kar[♦] and Ranjula Bali Swain^{*}

31 October 2014

In recent years growing competition in the microfinance industry has been censured for multiple borrowing, default crises, high interest rates and coercive recovery of loans. 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. Analysing the Microfinance Information Exchange data our empirical results show that increased competition in microfinance sector leads to a larger average loans and a decrease in the financial self-sustainability. The data also supports the view that increased competition in the microfinance industry leads to a decline in the loan portfolio quality.

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

JEL Classification: G21, G32.

[♦] Postdoctoral Researcher, Helsinki Center of Economic Research (HECER), P.O. Box 17 (Arkadiankatu 7) FI-00014, University of Helsinki, Finland. Email: ashim.kar@helsinki.fi

^{*} Associate Professor, Department of Economics, Box 513, S-75120, Uppsala, Sweden. Email: Ranjula.Bali@nek.uu.se

1. Introduction

By definition, in a competitive setting more firms compete for a limited market share. Particularly in the financial sector 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).

The microfinance industry has experienced a tremendous growth during the last few decades. Microfinance institutions (MFIs) are quasi-banks which provide specialized financial services, primarily to poor women, in developing countries. Subsidized funding from governments, development agencies and commercially oriented funders including commercial banks are the key drivers of growth in microfinance operations (Assefa et al., 2013; Ghosh and Van Tassel, 2011). Such rapid growth has induced increased competition among the MFIs, which has been blamed for multiple borrowing and a growing repayment crisis. Using country-level panel datasets compiled from the Microfinance Information Exchange (MIX) database, we employ the generalized methods of moments (GMM) estimation technique to investigate the impact of competition on microfinance institutions' (MFIs) outreach, financial performance and quality of loan portfolio.

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). The clustering effect may result in profit-motivated MFIs entering the markets where the penetration of the pre-existing socially-motivated MFIs 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).

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. 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 HHI (Boone et al., 2007). Thus, we later argue in the paper that these measures of competition may not assess existing competition scenarios in microfinance appropriately.

Amidst anecdotal speculation, the empirical evidence on competition in microfinance is scant. The paper attempts to fill this gap and contributes on several levels. First, though the Boone indicator has been employed for measuring competition in the banking sector (see, for example, Schaeck and Cihák, 2010; Boone and Leuvensteijn, 2010; Leuvensteijn et al. 2011), it has not been used before to estimate competition in the microfinance sector. Employing the Boone indicator enables us to move beyond proxying competition with concentration ratios like HHI and Lerner’s index. (as previously used in other studies, for instance, 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 generalized method of moments (IV-GMM) estimation approach. Third, the analysis is based on country-level panel datasets that combine three databases. The Microfinance Information Exchange (MIX) database provides the outreach, portfolio and balance sheet information on 521 individual MFIs. Additional data on institutional governance quality and macroeconomic and financial development were collected respectively from the World Governance Indicators and the World Development Indicators of the World Bank. Necessary adjustments have been made to guarantee consistency and comparability between these three data sets.

Our empirical results suggest that increased competition leads to an increase in average loan size (adjusted) which implies a movement away from the poor or worsened depth of outreach.

Several researchers and practitioners have expressed concern about increased competition especially through the entry of commercial banks into the Microfinance Industry. We also find that increased competition leads to a decline in the financial self-sustainability. Validating concerns and criticisms of increased competition, we find that increase in competition does in fact lead to a decline in the loan portfolio quality.

Subsequent sections discuss the relevant literature (section 2) and the various measures of competition (section 3). Section 4 presents the methodology with the estimation of our competition measures and the 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 seemed problematic for the microfinance sectors in many countries. 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. With increased competition, asymmetric information problems on clients’ profile escalate. As increased number of MFIs compete for the same set of clients, instances of multiple loans or ‘double dipping’ by borrowers rise. 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 induces the profitable clients of the socially-motivated MFIs to shift to the MFIs that lend larger loans and have higher net

returns. This thereby worsens the quality of the loan portfolio of the socially-motivated MFIs and negatively impacts these MFIs' cross-subsidisation possibilities¹ (Navajas et al., 2003; McIntosh and Wydick, 2005). Thus, increased competition leads to the risk of over-indebtedness and debt-traps with increased sociological and psychological constraints as stated before (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 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) finds 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 also lead the 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 further aggravated by bad staffs that encourage over-lending, offer wrong products, obscures loan terms and use abusive collection practices.

¹ Cross-subsidisation means reaching out to the unreached wealthier clients in order to finance a large number of poor clients with relatively small average loan size (Kar and Bali Swain 2013).

Hermes et al. (2008) analyse the impact of formal financial development on microfinance efficiency. They argue that in a formal market set up the efficiency of MFIs improves due to competitive pressure. In a related paper, Cull et al. (2009b) claim that MFIs faced with high competition from formal banks tend to reduce their breadth of outreach but focus more on the depth of outreach. However, they found that the effects on other performance indicators, such as profitability, are weak. Both Hermes et al. (2008) and Cull et al. (2009b), however, use country-level measures of competition, rather than measures reflecting competition at the institutional level.

Thus, we see from the above discussion that the impact of competition on the financial and social performance of MFIs remains grossly understudied. Although a few studies have attempted to explore these issues, they have some limitations, especially in terms of employing an appropriate tool for competition measurement. This paper aims to overcome this and adds to the empirical literature on microfinance performance and competition, and improves on the measurement of competition by using the Boone indicator, a recently developed measure of competition in the banking literature.

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 the 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. Some 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 (for example, 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, recent studies have increasingly relied on the NEIO approach 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's conduct directly. The parameters for the competitive behaviour of the firms—such as the price-cost margins—are estimated in the NEIO framework that include the Rosse-Panzar model, which provides an aggregate measure of competition, and the Lerner's index, which is an individual measure of market power.

Within the NEIO framework, there are two main methodologies. One is a simultaneous-equation approach which estimates the supply and demand functions to identify a parameter that measures the behaviour of the banks. The other is the Panzar and Rosse (1987) model that requires easily available data on the 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 measures competition by examining if a change in factor input prices influences the equilibrium revenues of a bank to measure competition. The value of the 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)².

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). Based on these views the X-

² See, for example, Tabak et al. (2012) and Bikker and Spierdijk (2008) for literature reviews.

efficiency literature is focused on the managerial ability to reduce production costs (Leuvensteijn et al., 2011). Another view suggests that high profits may indicate lack of competition. So, market power may also be related to profitability in the sense that profitability is measured as a ratio of price-cost margin (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. It centres on the idea that the more efficient firms (firms with lower marginal costs) gain higher market shares or profits.³ The higher the degree of competition in the market the stronger the impact and the more negative the indicator. Intuitively it implies that competition improves the performance of efficient firms, but 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:

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

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

³ The Boone (2008) model is founded essentially on the efficiency structure hypothesis of Demsetz (1973).

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 β is, the higher is the competition level in a market. Positive values for β suggest that higher the marginal costs of the bank, the more profits it will earn (Leuvensteijn 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:

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

We use return on assets (ROA) as the proxy for profits following Leuvensteijn et al (2011).⁴ The marginal cost (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 directly⁵. 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 assets⁶ (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 mean that costs increase (decrease) by the same proportion as the input prices increase (decrease). Hence, intuitively, total costs represent the three inputs included in the cost function. The TCF is specified as follows:

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

⁴ The dependent variable is computed as $\log(1+ROA_{it})$ to avoid negative values of return on assets in the log specification.

⁵ Schaeck and Cihak (2010) approximate a firm's marginal costs by the ratio of average variable costs to total income.

⁶ Financial expenses include interest expenses which is the direct measure of 'price of funds'. However, the data set does not have a separate measure of interest expenses.

where TC_{it} stands for total costs (captured by the total expenditures over assets ratio) of MFI i at year t ⁷, 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.

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:

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

Leuvensteijn 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 instrumental variables need to be employed with a two-step GMM estimator. We use the lagged values of MC_{it} as the instruments based on formal endogeneity tests. If, however, formal tests do not suggest any endogeneity as such, we choose to use a linear fixed-effects model (i.e., the

⁷ Total costs are the sum of personnel expenses, other non-interest expenses, and interest expenses.

within estimator) as using IV estimates with GMM technique in unjustified then. The marginal costs are computed by substituting parameter estimates from TCF into equation (4).

4.2 Model Specification

To evaluate the effect of competition on the performance indicators of microfinance institutions, we estimate the following model:

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

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 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_e^2 ; 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_u^2 ; 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_ε^2 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 indicates that panel data estimations should be employed. However, an additional difficulty in estimating the model is that the measures of financial performance, depth of outreach and loan portfolio quality of MFIs 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. Thus, 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 χ^2 with $(L - K)$ degrees of freedom. A high value of χ^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 individual effects 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 voluntarily reported to the Microfinance Information Exchange database⁸. 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, 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 quality⁹. Country-level data on institutional governance quality and macroeconomic and financial development were collected from the Worldwide Governance Indicators and the World Development Indicators databases of the World Bank. Initially, we had data for 15 years (1996-2010) from 1144 MFIs which have been currently in operation in 35 countries (7146 observations). In the final dataset, however, 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 include 28 observations on MFIs which have less than level-3 diamonds disclosure rating¹⁰. 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 used the first and second lagged values as the instruments, our database reduces to 3001 observations for 2003 to 2010. The number of sampled countries was also reduced. Thus, our resulting final sample for estimating the Boone indicator is an unbalanced panel¹¹ of 521 MFIs from 10 countries (Bangladesh, India, Nepal, Indonesia, Philippines, Bolivia, Ecuador, Mexico, Nicaragua and Peru), totalling 3001 observations. Our results need to be qualified by the limitation that we did not take subsidies, donations and grants into account while calculating the MFIs’ real return on assets. This is due to the fact that MIX data does not share the subsidy and grants component. This implies that our measure of FSS in effect reflects operational self-sufficiency. Moreover, the MIX data is biased towards self-sufficient and commercially oriented MFIs and dominated by Latin American MFIs. Table 1 provides information on the

⁸ Individual MFI data are maintained in their publicly available information platform: www.mixmarket.org.

⁹ 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>

¹⁰ This study sampled MFIs which have 5-diamonds (20.96%), 4-diamonds (42.09%), 3-diamonds (36.02%) and less than 3-diamonds (0.93%) disclosure ratings.

¹¹ Some MFIs report information for a minimum of 3 years while others report for 4-8 years.

number of observations by country and year. Details on the number of observations by country and MFI legal types are presented in Table 2.

This set of countries has differences in their regulatory frameworks and revenue streams. However, when we employ the Boone indicator to measure competition, differences in country-specific revenue sources do not matter significantly. Thus we can compare the revenue stream of a ‘micro-saving’ centric country (Indonesia), for instance, with that of a ‘microloan’ centric country (India). Our data includes countries where the microfinance sectors are getting increasingly competitive and characterized by differing levels of concentration. Moreover, these countries have varying magnitudes of population, GDP and footprint of the microfinance sectors. For example, India is one of the largest countries in the world, with a population of around 1.27 billion in 2013, while 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 two 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. Depth of outreach increases as the percentage of female borrowers increases, whereas larger average loan size implies a movement towards economically better-off borrowers and hence a decline in the 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 employs 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, MFI characteristics, macroeconomic indicators and governance indicators.

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. The variable definitions are provided in table 3 and table 4 provides the summary statistics of the dependent and the explanatory variables used in the regression analyses. For example, the data consists of MFIs of different levels of maturity, ranging from very new to very mature (61 years). In terms of the focus on lending, MFIs in the sample are of diversified categories, ranging from MFIs with no lending to MFIs which lend as high as 25 percent of their total assets.

6. Discussion on empirical results

6.1 Boone coefficient scores

To estimate the Boone indicator we need to estimate the marginal costs for each MFI and year in our data. However, since marginal costs are not directly observed, it is estimated using a separate translog cost function. 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. On the contrary, gross loan portfolios in Nepal and Philippines are the lowest. Administrative expenses in terms of total assets are comparatively high in Latin American countries, especially in Mexico (around 15%) and Nicaragua (around 9%). In Bangladesh, India and Nepal administrative expenses are relatively low (ranging between 2% to 5% only). Financial expenses for the MFIs in Nepal and Bangladesh are among the lowest (2.5% and 3.8% respectively). These expenses are more-or-less similar in three Latin American countries: Peru, Nicaragua and Mexico (around 6%). In terms of personnel expenses, Mexico (around 21%) tops the list while MFIs in Nepal with an average of 5% personnel expenses are amongst the lowest. The Boone scores in table 6 confirm that the included MFIs are highly competitive (negative Boone-scores) although on average MFIs in Mexico and Indonesia show greater collusion (positive Boone scores).

Table 7 presents the historical evolution of the Boone scores by country for the whole period (2003-10). In recent years microfinance 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 instead show a tendency to collude in certain years. Table 8 presents the cross-correlations between our main independent variables used in the econometric model along with their corresponding significance levels.

6.2 Competition and MFI-performance analysis

The results of 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 used for estimations in order to control for overall macroeconomic environment and institutional quality. At the outset, diagnostic tests were employed 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 earlier, higher negative values of the Boone indicator indicate increased competition. Results in Table 9 (dependent variable: percent of female borrowers) shows that the coefficients of the Boone indicator variable in columns 1-3 are negative, but statistically insignificant. However, the results for the adjusted average loan size are negative and highly significant except for model 3. As Boone indicator decreases (higher levels of competition) the average loan size increases. This result raises concerns about the MFIs in these countries. Evidence indicates a decline in the lending

operations to the relatively poor as depth of outreach decreases (increase in the average loan) due to increased competition. Depth of outreach also decreases with the increase in real yield. The coefficients for the size variable are always positive and significant in model 2 of the female borrowers' regressions. Size coefficients are highly significant in average loan size regressions. Furthermore, with the increase in the MFI size (in terms of total assets) the female participation improves (increase in depth of outreach), but the average loan size increases. Thus even though MFIs continue to maintain their focus on women as their major clients, average loan size has risen. This implies that either the women that are better-off are now getting loans or the women are in a better position to afford bigger loans. We also find interesting results 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. Better control of corruption is linked with higher average loan size. Other variables, however, do not seem to have any significant effect on the depth of outreach measures.

The results for the financial performance of MFIs in terms of FSS and ROA are presented in table 10. As the Boone indicator becomes more positive (indicating greater collusion) the MFIs' self-sufficiency and profitability increases. One plausible explanation for this is that the MFIs in the sampled countries have not yet reached a level where with increased market power profit margins have declined enough to encourage the MFIs to provide risky loans. The increased market power enables the MFIs to maintain cautious lending operations through smaller loans. It may therefore be possible for them to earn some returns to become self-sufficient. An increase in the real portfolio yields therefore helps to improve the MFIs' self-sustainability. The focus on lending also shows similar results. 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 presents 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 mostly negative and highly significant. Our empirical results indicate that as the Boone indicator becomes more negative (increased competition) MFIs' are confronted with increase in loan portfolio risk. High default in MFIs implies low loan portfolio quality. As documented for several MFIs, increased competition may lead to dual or multiple borrowing resulting in heavy debt burden for the borrowers. Some borrowers also get into the cycle of repaying old loans with new ones. Such measures result in unhealthy borrowing and lead to a decline in loan portfolio quality. This supports the researchers and practitioners that have cautioned against indiscriminate lending with increased competition that may lead to default crisis and coercive recovery of loans. Among the control variables, we also find that for older MFIs repayment performance is better and such performance has an increasing trend (as the coefficients of the age² 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 larger MFIs have a better loan portfolio quality or better monitoring capability than the smaller ones. We also find that as rural population grow 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

As the microfinance Industry scales up to reach larger number of clients, entry of new MFIs is leading to increased competition. The paper aims at determining the impact of competition on MFIs' depth of outreach, financial performance and quality of loan portfolio. 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. We employ a new and relatively advanced technique of competition measurement in the microfinance industry, the Boone indicator. The existing endogeneity issues in the estimation are also accounted for. We first estimate the 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. The analysis uses MIX Market data for 521 MFIs in 10 selected countries with a vibrant presence of microfinance activities between 2003 and 2010. 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 seems to have declined as average loan size increases, the effect of competition on female participation remains statistically insignificant.

Our results confirm that competition in the microfinance industry might lead to a negative impact on MFIs performance and portfolio quality. The concerns regarding increased competition leading to multiple borrowing, default crisis, high interest rates and coercive recovery of loans may have some substance. However, these negative effects of increased competition may be minimized through improved regulatory measures. As previous studies suggest, sharing information among the MFIs may also potentially contribute to lower delinquency rates as well as prevent borrowers from taking multiple loans and getting into debt traps.

References

- Assefa, E., Hermes, N. and Meesters, A. (2013). "Competition and the Performance of Microfinance Institutions", *Applied Financial Economics*, 23(9): 767-782.
- Baltagi, B.H. 2008. *Econometric analysis of panel data*. New York: Wiley.
- Baquero, G., Malika H. and Andréas H. (2012). "Competition, Loan Rates and Information Dispersion in Microcredit Markets." European School of Management and Technology Working Paper No. 12-02. Berlin.
- Belotti, F., Silvio D., Giuseppe I. and Vincenzo A. (2012). "Stochastic frontier analysis using Stata", Centre for Economic and International Studies, Research Paper Series, Vol. 10, Issue 12, No. 251.
- Berger, A. N., K. Lapper, L. F. and Turk-Ariss, R. (2009). "Bank Competition and Financial stability", *Journal of Financial Services Research* 35: 99-118.
- Bikker, J.A. and M. von Leuvensteijn (2008). Competition and efficiency in the Dutch life insurance industry. *Applied Economics* 40: 2063-2084.
- Bikker, J. A. and Spierdijk, L. (2008). How banking competition changed over time, DNB Working Paper No. 167, De Nederlandsche Bank, Amsterdam.
- Bikker, J. A., Laura Spierdijk and P. Finnie (2007). The impact of market structure, contestability and institutional environment on banking competition", Working Papers 07-29, Utrecht School of Economics.
- Bikker, J.A. and Bos, J.W.B. (2005). "Competition and Efficiency in Banking: International Comparisons", *Economic and Financial Modelling*, 12(3):103-48.
- Boone, J., J. van Ours and H. van der Wiel (2007). "How (not) to measure competition",

Tilburg University, Tilburg Law and Economics Center (TILEC) Discussion Paper No.2007–014.

- Boone, J. (2008). A new way to measure competition. *Economic Journal* 118, 1245–1261.
- Boone, J. and M. van Leuvensteijn (2010). “Measuring competition using the profit elasticity: American sugar industry, 1890–1914”, CEPR Discussion Paper Series No.8159.
- Bresnahan, T. F. (1982). The oligopoly solution concept is identified, *Economics Letters*, 10, 87–92.
- Broecker, T. (1990). “Credit-worthiness tests and interbank competition”, *Econometrica*, 58(2): 429-452.
- Carbó V., S. D. Humphrey, J. Maudos, and P. Molyneux (2009). “Cross-country comparisons of competition and pricing power in European banking”, *Journal of International Money and Finance*, 28(1), 115–134.
- Cetorelli, N. (2001). Competition among banks: good or bad?, Federal Reserve Bank of Chicago, *Economic Perspectives*, 2, 38–48.
- Claessens, S. and Laeven, L. (2004). What drives bank competition? Some international evidence. *Journal of Money, Credit, and Banking* 36, 563–583.
- Cull, R., Demirguc-Kunt, A., and Morduch, J. (2007). “Financial performance and outreach: A global analysis of lending microbanks”, *Economic Journal*, 117: 107-133.
- Cull, R., Demirguc, -Kunt, A. and Morduch, J. (2009a). Microfinance meets the market, *Journal of Economic Perspectives*, 23, 167–92.
- Cull, R., Demirguc, -Kunt, A. and Morduch, J. (2009b). Banks and microbanks, Policy Research Working Paper No. 5078, World Bank.
- Delis, M. D., K. Chrostos Staikouras, Panagiotis T., and Varlagas (2008). “On the measurement o market power in the banking industry”, *Journal of Business, Finance and Accounting*, 35(7) & (8): 1023-1047.
- Demsetz, H. (1973). Industry structure, market rivalry, and public policy. *Journal of Law and Economics*, 16: 1–9.
- Ghosh, Suman and Eric Van Tassel (2012). “Funding microfinance under asymmetric information”, *Journal of Development Economics*, 101 (March): 8–15.
- Goldberg, L. G. and Rai, A. (1996). The structure-performance relationship for European banking, *Journal of Banking and Finance*, 20: 745-71.
- Hannan, T. (1991). “Foundations of the Structure-Conduct-Performance Paradigm in Banking”, *Journal of Money, Credit and Banking*, 23: 68-84.
- Hansen, L.P. (1982). Large sample properties of generalized method of moments estimators.

Econometrica 50: 1029–54.

- Hermes, Niels, Lensink, Robert and Meesters, Aljar (2008). “Outreach and Efficiency of Microfinance Institutions”, *Centre for International Banking, Insurance and Finance Working Paper*.
- Hoff, K. and Stiglitz, J. (1998). “Moneylenders and bankers: Price-increasing subsidies in a monopolistically competitive market”, *Journal of Development Economics*, 55(2): 485-518.
- Kahnemann, Daniel and Tversky, Amos (1979). “Prospect Theory: An Analysis of Decisions under Risk” *Econometrica*, 47(2): 263-291.
- Lau, L. (1982). On identifying the degree of competitiveness from industry price and output data, *Economics Letters*, 10: 93–9.
- Leuvensteijn, M.V., Bikker, J., Rixtel, A.V., Sorensen, C.K., 2011. “A new approach to measuring competition in the loan markets of the Euro area”, *Applied Economics*, 43(23): 3155–3167.
- Marquez, R. (2002). “Competition, adverse selection, and information dispersion in the banking industry”, *Review of Financial Studies*, 15(3): 901-926.
- McIntosh, Craig, de Janvry, Alain and Sadoulet, Elizabeth (2005). “How Rising Competition among Microfinance Institutions Affects Incumbent Lenders”, *Economic Journal* 115(506): 987-1004.
- McIntosh, Craig and Wydick Bruce (2005). “Competition and Microfinance”, *Journal of Development Economics*, 78: 271- 298.
- Navajas, Sergio, Conning, Jonathan and Gonzalez-Vega, Claudio (2003). “Lending technologies, competition and consolidation in the market for microfinance in Bolivia”, *Journal of International Development*, 15:747-770.
- Olivares-Polanco, F. (2005). “Commercializing microfinance and deepening outreach? Empirical evidence from Latin America”, *Journal of Microfinance*, 7: 47-69.
- Panzar, J. C. and Rosse, J. N. (1987). Testing for ‘monopoly’ equilibrium, *Journal of Industrial Economics*, 35, 443–56.
- Schaeck, K. and M. Cihák (2010). “Competition, efficiency and soundness in banking: An industrial organisation perspective”, Tilburg University European Banking Center Discussion Paper No.2010–20S.
- Schicks, Jessica and Rosenberg, Richard (2011). “Too much Microcredit? A Survey of the Evidence on Over-Indebtedness”, *CGAP Occasional Paper No. 19*, September 2011.
- Tabak, Benjamin M., Dimas M. Fazio, Daniel O. Cajueiro (2012). “The relationship between banking market competition and risk-taking: Do size and capitalization matter?” *Journal of Banking and Finance*, 36 (12): 3366–3381.

Vogelgesang, Ulrike (2003): “Microfinance in Times of Crisis: The Effects of Competition, Rising Indebtedness, and Economic Crisis on Repayment Behavior”, *World Development*, 31(13): 2085–2114.

Wooldridge, J.M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: The MIT Press.

TABLES

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					Observations
	NGO	NBFI	Bank	RB	CU-Coop & Others	
Bangladesh	289	0	8	0	5	302
Bolivia	93	38	24	0	12	167
Ecuador	101	0	32	0	164	297
India	259	223	6	8	51	547
Indonesia	25	0	0	165	24	214
Mexico	35	178	12	0	11	236
Nepal	63	42	19	44	48	216
Nicaragua	140	14	14	0	23	191
Peru	124	218	8	0	51	401
Philippines	177	0	13	234	6	430
Observations	1306	713	136	451	395	3001

Notes. NGO: Non-government Organizations, NBFI: Non-bank Financial Institutions, RB: Rural Bank, CU-Coop: Credit Union/Cooperatives.

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).	Author's calculations
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	MIX Market
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 in percentage)	WDI
Control of corruption index	Aggregate governance indicator of 'control of corruption'	WGI
Political stability index	Aggregate governance indicator of 'political stability'	WGI
Regulatory quality index	Aggregate governance indicator of 'regulatory quality'	WGI
Rule of law index	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
<i>Dependent variables</i>					
Female borrower	2435	0.75	0.26	0	1.27
Average loan (adj.)	2904	0.41	0.67	0	9.98
FSS	2099	0.92	0.27	-0.47	4.91
ROA	2533	0.02	0.08	-1.01	0.56
PAR30	2628	0.07	0.11	0	1
PAR90	2137	0.05	0.09	0	0.99
<i>Explanatory variables</i>					
Boone indicator	3001	-0.01	0.02	-0.09	0.11
Real yield	2032	0.26	0.18	-0.11	1.19
Loan-to-assets ratio	3000	0.77	0.52	0	24.94
Size	3001	15.54	1.94	0	21.25
Age	2984	15.34	10.86	0	61
Growth of GDP p.c.	3001	3.97	2.76	-5.89	9.13
Inflation	3001	0.06	0.03	-0.02	0.18
R. population growth	3001	0.53	0.68	-0.52	2.00
Domestic credit	3001	45.06	17.37	14.42	71.84
Spread	2324	8.50	5.46	3.90	22.94
Control of corruption	3001	-0.62	0.31	-1.49	-0.10
Political stability	3001	-1.14	0.46	-2.12	-0.09
Regulatory quality	3001	-0.35	0.46	-1.28	0.46
Rule of law	3001	-0.59	0.37	-1.25	0.19

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

Notes. GLP: Gross Loan Portfolio, AEA: Administrative Expenses to Assets Ratio, FEA: Financial Expenses to Assets Ratio and PEA: Personnel Expenses to Assets Ratio. 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	<u>Bangladesh</u>		<u>India</u>		<u>Nepal</u>		<u>Indonesia</u>	
	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	<u>Philippines</u>		<u>Bolivia</u>		<u>Ecuador</u>		<u>Mexico</u>	
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	<u>Nicaragua</u>		<u>Peru</u>	
	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

Notes. RY: Real yield, L/A: Loans to assets ratio (focus on lending), INF: Rate of inflation, RP: Percent of rural population in terms of total population, DC: Domestic credit, SP: Interest rate spread, CC: Control of corruption index, PS: Political stability index, Rule: Rule of law index, REG: regulatory status.

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 (0.550)	-0.441 (0.340)	-0.232 (0.180)	-1.447* (0.597)	-1.969*** (0.509)	0.346 (0.441)
Real yield	-0.845 (0.697)	-0.809 (0.655)	0.233 (0.228)	-0.498** (0.171)	-0.527** (0.172)	-0.242 (0.244)
Log of loans/assets ratio	-0.029 (0.046)	-0.024 (0.043)	-0.022 (0.026)	0.016 (0.428)	-0.011 (0.450)	0.001 (0.899)
Size	0.092* (0.047)	0.085 (0.046)	0.033* (0.016)	0.174*** (0.045)	0.179*** (0.046)	0.068* (0.032)
Log of age	-1.120 (0.597)	-1.114 (0.694)	-0.365 (0.216)	-0.372 (0.237)	-0.386 (0.236)	-0.140 (0.162)
Age-squared	0.348 (0.200)	0.351 (0.233)	0.123 (0.086)	0.143 (0.089)	0.148 (0.088)	0.075 (0.072)
Growth of GDP per capita	0.002 (0.004)	0.004 (0.003)		-0.002 (0.006)	-0.003 (0.005)	
Inflation	-0.250 (0.233)	-0.244 (0.192)		-0.357 (0.349)	-0.106 (0.291)	
Rural population growth	-0.111 (0.161)	-0.087 (0.145)		-0.106 (0.177)	-0.148 (0.171)	
Domestic Credit	-0.001 (0.001)	-0.001 (0.002)		-0.006* (0.002)	-0.006* (0.003)	
Interest Rate Spread	0.001 (0.006)	0.004 (0.006)		0.005 (0.010)	0.002 (0.007)	
Control of Corruption	0.025 (0.098)		-0.088* (0.045)	0.117 (0.096)		0.184* (0.081)
Political Stability	0.021 (0.040)		0.016 (0.027)	-0.022 (0.065)		-0.028 (0.051)
Regulatory Quality	0.002 (0.158)		-0.175* (0.081)	-0.159 (0.101)		0.089 (0.091)
Rule of Law	-0.101 (0.185)		0.169* (0.066)	0.179 (0.113)		0.207 (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)

Notes. 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* (0.431)	0.962** (0.355)	0.161 (0.292)	0.436** (0.147)	0.436 (0.268)	0.343* (0.152)
Real yield	0.308** (0.103)	0.247* (0.097)	0.421** (0.135)	0.125** (0.048)	-0.659 (0.470)	0.345 (0.279)
Log of loans/assets ratio	0.473* (0.237)	0.439 (0.227)	0.659 (0.425)	0.254* (0.104)	-0.353 (0.305)	0.022 (0.020)
Size	0.099** (0.032)	0.097** (0.033)	0.108*** (0.021)	0.045** (0.016)	0.022 (0.042)	0.032* (0.013)
Log of age	0.329 (0.178)	0.348 (0.183)	0.280* (0.129)	0.065 (0.106)	0.271 (0.266)	0.111 (0.058)
Age-squared	-0.172* (0.070)	-0.161* (0.071)	-0.133* (0.055)	-0.047 (0.037)	-0.089 (0.090)	-0.044* (0.022)
Growth of GDP per capita	0.007 (0.004)	0.007* (0.003)		0.003 (0.002)	0.000 (0.003)	
Inflation	-0.308 (0.215)	-0.219 (0.175)		-0.039 (0.056)	-0.183 (0.158)	
Rural Population Growth	0.113 (0.119)	0.054 (0.099)		0.015 (0.035)	-0.159 (0.127)	
Domestic Credit	0.002 (0.002)	0.003 (0.002)		0.000 (0.001)	0.001 (0.001)	
Interest Rate Spread	-0.005 (0.006)	-0.000 (0.005)		-0.001 (0.002)	-0.001 (0.004)	
Control of Corruption	-0.029 (0.074)		-0.145* (0.060)	-0.007 (0.019)		-0.037 (0.026)
Political Stability	-0.002 (0.048)		0.036 (0.034)	0.002 (0.014)		0.006 (0.018)
Regulatory Quality	-0.250*** (0.068)		-0.222*** (0.062)	-0.062** (0.024)		-0.117* (0.055)
Rule of Law	0.129 (0.084)		0.173* (0.076)	0.077** (0.028)		0.061 (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)

Notes. 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 (0.323)	-0.740** (0.257)	-0.799*** (0.203)	-0.416 (0.275)	-0.714** (0.223)	-0.764*** (0.186)
Real yield	0.436 (0.345)	0.393 (0.327)	0.036 (0.243)	0.258 (0.305)	0.261 (0.288)	-0.011 (0.224)
Log of loans/assets ratio	0.067 (0.045)	0.065 (0.045)	0.017 (0.038)	0.075 (0.040)	0.073 (0.041)	0.027 (0.035)
Size	0.015 (0.029)	0.024 (0.029)	0.010 (0.017)	0.017 (0.026)	0.024 (0.027)	0.005 (0.016)
Log of age	0.248 (0.273)	0.257 (0.300)	-0.196** (0.066)	0.112 (0.226)	0.125 (0.254)	-0.184** (0.063)
Age-squared	-0.075 (0.088)	-0.079 (0.094)	0.080* (0.032)	-0.024 (0.071)	-0.030 (0.078)	0.080** (0.030)
Growth of GDP per capita	-0.000 (0.003)	-0.002 (0.002)		0.000 (0.002)	-0.002 (0.002)	
Inflation	0.098 (0.159)	0.069 (0.136)		0.010 (0.139)	0.021 (0.118)	
Rural Population Growth	0.294*** (0.087)	0.277** (0.087)		0.237** (0.072)	0.217** (0.073)	
Domestic Credit	-0.000 (0.001)	0.000 (0.001)		-0.001 (0.001)	-0.000 (0.001)	
Interest Rate Spread	0.007* (0.003)	0.003 (0.003)		0.008** (0.003)	0.004 (0.003)	
Control of Corruption	-0.047 (0.065)		-0.024 (0.043)	-0.017 (0.058)		-0.015 (0.038)
Political Stability	-0.016 (0.035)		0.002 (0.026)	-0.028 (0.029)		-0.008 (0.024)
Regulatory Quality	-0.033 (0.064)		0.004 (0.052)	-0.015 (0.058)		0.005 (0.048)
Rule of Law	0.156 (0.082)		0.025 (0.055)	0.108 (0.072)		0.002 (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)

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

APPENDIX

Table A1: Mean and standard deviations of country-environment variables

Country	GDP growth	L/A	Rural Pop.	Agri. VA	CAR
Bangladesh	6.054 (0.408)	0.777 (0.108)	73.903 (0.980)	19.991 (1.065)	0.191 (0.154)
Bolivia	4.409 (0.898)	0.800 (0.108)	35.000 (0.958)	13.852 (0.862)	0.276 (0.224)
Ecuador	3.831 (2.171)	0.810 (0.112)	35.121 (1.377)	10.174 (0.619)	0.296 (0.211)
India	8.356 (2.019)	0.862 (1.174)	70.145 (0.716)	18.396 (0.733)	0.213 (0.780)
Indonesia	5.615 (0.585)	0.734 (0.117)	52.942 (1.591)	14.080 (0.863)	0.243 (0.191)
Mexico	2.113 (3.299)	0.714 (0.155)	22.949 (0.558)	3.396 (0.091)	0.356 (0.266)
Nepal	4.299 (0.941)	0.697 (0.222)	84.336 (0.661)	35.015 (1.635)	0.102 (0.116)
Nicaragua	3.354 (2.282)	0.789 (0.118)	43.638 (0.577)	17.741 (0.604)	0.279 (0.179)
Peru	6.691 (2.924)	0.791 (0.123)	24.261 (0.829)	7.138 (0.232)	0.305 (0.232)
Philippines	5.055 (1.859)	0.684 (0.143)	51.744 (0.216)	12.790 (0.368)	0.223 (0.151)

Notes. L/A = Loans to assets ratio.

WORKING PAPERS*

Editor: Nils Gottfries

- 2012:18 Gunnar Du Rietz, Magnus Henrekson and Daniel Waldenström, The Swedish Inheritance and Gift Taxation, 1885–2004. 47pp.
- 2012:19 Helge Bennmärker, Erik Grönqvist and Björn Öckert, Effects of contracting out employment services: Evidence from a randomized experiment. 55 pp.
- 2012:20 Pedro Carneiro and Rita Ginja, Partial Insurance and Investments in Children. 32pp.
- 2013:1 Jan Pettersson and Johan Wikström, Peeing out of poverty? Human fertilizer and the productivity of farming households. 43 pp.
- 2013:2 Olof Åslund and Mattias Engdahl, The value of earning for learning: Performance bonuses in immigrant language training. 52 pp.
- 2013:3 Michihito Ando, Estimating the effects of nuclear power facilities on local income levels: A quasi-experimental approach. 44 pp.
- 2013:4 Matz Dahlberg, Karin Edmak and Heléne Lundqvist, Ethnic Diversity and Preferences for Redistribution: Reply. 23 pp.
- 2013:5 Ali Sina Önder and Marko Terviö, Is Economics a House Divided? Analysis of Citation Networks. 20 pp.
- 2013:6 Per Engström and Eskil Forsell, Demand effects of consumers' stated and revealed preferences. 27 pp.
- 2013:7 Che-Yuan Liang, Optimal Inequality behind the Veil of Ignorance. 26 pp.
- 2013:8 Pia Fromlet, Monetary Policy Under Discretion Or Commitment? -An Empirical Study. 57 pp.
- 2013:9 Olof Åslund and Mattias Engdahl, Open borders, transport links and local labor markets. 41 pp.
- 2013:10 Mohammad Sepahvand, Roujman Shahbazian and Ranjula Bali Swain, Time Investment by Parents in Cognitive and Non-cognitive Childcare Activities. 31 pp.
- 2013:11 Miia Bask and Mikael Bask, Social Influence and the Matthew Mechanism: The Case of an Artificial Cultural Market. 13 pp
- 2013:12 Alex Solis, Credit access and college enrollment. 54 pp
- 2013:13 Alex Solis, Does Higher Education Cause Political Participation?: Evidence From a Regression Discontinuity Design. 48 pp.

* A list of papers in this series from earlier years will be sent on request by the department.

- 2013:14 Jonas Kolsrud, Precaution and Risk Aversion: Decomposing the Effect of Unemployment Benefits on Saving. 37 pp.
- 2013:15 Helena Svaleryd, Self-employment and the local business cycle. 28 pp.
- 2013:16 Tobias Lindhe and Jan Södersten, Distortive Effects of Dividend Taxation. 22 pp.
- 2013:17 Jonas Poulsen, After Apartheid: The Effects of ANC Power. 42 pp.
- 2013:18 Magnus Gustavsson, Permanent versus Transitory Wage Differentials and the Inequality-Hours Hypothesis. 11 pp.
- 2013:19 Lovisa Persson, Consumption smoothing in a balanced budget regime. 35 pp.
- 2013:20 Linuz Aggeborn, Voter Turnout and the Size of Government. 50 pp.
- 2013:21 Niklas Bengtsson, Stefan Peterson and Fredrik Sävje, Revisiting the Educational Effects of Fetal Iodine Deficiency. 48 pp.
- 2013:22 Michihito Ando, How Much Should We Trust Regression-Kink-Design Estimates? 69 pp.
- 2013:23 Bertil Holmlund, What do labor market institutions do? 25 pp.
- 2014:1 Oscar Erixson and Henry Ohlsson, Estate division: Equal sharing as choice, social norm, and legal requirement. 45 pp.
- 2014:2 Eva Mörk, Anna Sjögren and Helena Svaleryd, Parental unemployment and child health. 35 pp.
- 2014:3 Pedro Carneiro, Emanuela Galasso and Rita Ginja, Tackling Social Exclusion: Evidence from Chile. 87 pp.
- 2014:4 Mikael Elinder och Lovisa Persson, Property taxation, bounded rationality and housing prices. 38 pp.
- 2014:5 Daniel Waldenström, Swedish stock and bond returns, 1856–2012. 51 pp.
- 2014:6 Mikael Carlsson, Selection Effects in Producer-Price Setting. 34 pp.
- 2014:7 Ranjula Bali Swain and Fan Yang Wallentin, The impact of microfinance on factors empowering women: Differences in regional and delivery mechanisms in India's SHG programme. 28 pp.
- 2014:8 Ashim Kumar Kar and Ranjula Bali Swain, Competition, performance and portfolio quality in microfinance markets. 33 pp.

See also working papers published by the Office of Labour Market Policy Evaluation
<http://www.ifau.se/>

ISSN 1653-6975