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Competitiveness in Microfinance Markets: A Non-structural Approach

Ashim Kumar Kar[a] and Ranjula Bali Swain[b]

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In this paper we adopt the Panzar-Rosse revenue tests, a widely used non-structural model, to assess the competitive conditions in five vibrant microfinance markets, namely India, Indonesia, Philippines, Peru and Ecuador, over the period 2005-2009. The degree of competitiveness is assessed on the basis of the revenue elasticity to input prices. We also relate revenue with capitalisation and risk indicators. In addition with the static model, we propose a dynamic version of the model to see how the PR indicator vary over longer periods of observation. Using disaggregated panel data from 342 Microfinance Institutions (MFIs) of the above countries estimations show that the microfinance markets in India and Indonesia can be both monopolistic and monopolistically competitive. However, in Philippines and Ecuador microfinance markets generally operate under conditions of monopoly while Peru's market is monopolistically competitive. These results have noteworthy implications for the performance of MFIs in the selected countries. From a theoretical point of view, monopolistic competition may ensure further growth of the industry, as there are many underserved clients, but with lower profitability. However, businesses may not be viable due to low profitability. On the contrary, lack of competition may contribute to the inefficiency of MFIs with high profitability. Therefore, MFIs' social performance could be seriously damaged.

JEL classification: D4; G21; L11; N20; O16

Keywords: microfinance, competition, market structure, market power estimation, panel data, dynamic panel estimation, Panzar-Rosse revenue tests.

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[a]Postdoctoral Researcher, Helsinki Center for Economic Research (HECER), University of Helsinki, Arkadiankatu 7, FI-00101 Finland. E-mail: ashim.kar@helsinki.fi. This research was partly funded by the Academy of Finland.
[b]Professor, Department of Economics, Södertörn University and Uppsala University, Email: Ranjula.Bali@nek.uu.se.

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In this paper we adopt the Panzar-Rosse revenue tests, a widely used non-structural model, to assess the competitive conditions in five vibrant microfinance markets, namely India, Indonesia, Philippines, Peru and Ecuador, over the period 2005-2009. The degree of competitiveness is assessed on the basis of the revenue elasticity to input prices. We also relate revenue with capitalisation and risk indicators. In addition with the static model, we propose a dynamic version of the model to see how the PR indicator varies over longer periods of observation. Using disaggregated panel data from 342 MFIs of the above countries estimations show that the microfinance markets in India and Indonesia can be both monopolistic and monopolistically competitive. However, in Philippines and Ecuador microfinance markets generally operate under conditions of monopoly while Peru's market is monopolistically competitive. These results have noteworthy implications for the performance of MFIs in the selected countries. From a theoretical point of view, monopolistic competition may ensure further growth of the industry, as there are many underserved clients, but with lower profitability. However, businesses may not be viable due to low profitability. On the contrary, lack of competition may contribute to the inefficiency of MFIs with high profitability. Therefore, MFIs' social performance could be seriously damaged.

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1. Introduction

The microfinance industry has experienced tremendous growth in the last few decades and competition among the microfinance institutions (MFIs) is getting fierce day by day. In a competitive situation more firms compete for a limited market share and thus firms are to lower prices to equal marginal revenue and marginal costs. So, increased competition should bring in some benefits for microfinance clients such as better access to credit and lower interest rates. Empirical studies have confirmed this as predicted. However, alongside bringing some positive impacts increased competition in microfinance has also introduced new problems.

Increase in competition amongst MFIs affects their outreach, performance and portfolio quality in several ways (Hartarska and Mersland, 2012; Hermes et al., 2011; Assefa et al., 2013). First, the socially-motivated MFIs fail to lend to the poorest and potentially least-profitable borrowers. Second, profitable and more productive borrowers of the socially-motivated MFIs are induced to shift to their for-profit counterparts who typically target wealthier clients and offer larger loans. Such transfer worsens the portfolio quality of the socially-motivated MFIs. With increased competition the interest rates charged by the MFIs drop, so their overall profitability and ability to cross-subsidise worsens (Navajas et al., 2003; Vogelgesang, 2003; McIntosh and Wydick, 2005). Increased competition thus may lead to mission drift concerns since too much market power negatively affects small businesses' and poor households' access to financial services and, consequently, socially-motivated MFIs' missions can be greatly affected. Third, information asymmetries and the lack of informational exchange among the MFIs increase due to stronger competition, with more MFIs competing for the same set of clients. This eventually escalates the number of multiple loans or 'double dipping' by the borrowers. Fourth, competition may weaken the functioning of the dynamic incentive mechanism[1] and lead to increased loan default. Excessive total debt due to multiple loans, leads to a further deterioration in the total default rate of the MFIs, leading to a dysfunction of the dynamic incentives mechanism (Hoff and Stiglitz, 1998).

The impact of competition on MFIs' outreach and performance and the prevailing market structure, in which MFIs operate, has been investigated only to a limited extent. Interest in studying competitive conditions in microfinance markets (whether markets are competitive, collusive or monopolistic) has primarily been constrained by unavailability of industry- and firm-level data. Utilising rating agency data, Mersland and Strom (2012) use the Panzar-Rosse revenue tests (PR-

[1] 'Dynamic incentives' link clients' future access to credit with proper repayments of earlier loans to discipline them and ensure repayments on time.

RT) to examine whether MFIs' can attain profitability incompatible with perfect competition by charging prohibitive lending rates. Other than this study, the evidence on microfinance market structure is limited and mostly anecdotal. So it is crucial to explore the degrees, causes and consequences of competitiveness, or the likely presence of anti-competitive behaviour and inefficiency, in different microfinance markets as this may impose severe costs in this globalised and flourishing industry.

Measuring competition is complex. The banking literature investigates competitive behaviour by applying the conduct-parameter-method (CPM) and the Panzar-Rosse revenue tests PR-RT[2]. However, similar research in microfinance markets is scanty. Employing the PR-RT to the MFI-level panel data corresponding to the microfinance sectors in India, Indonesia, Philippines, Peru and Ecuador for the period 1996-2010 we present inter-country comparison of competitiveness of the microfinance markets. Microfinance markets in these countries are highly competitive and vibrant, and the number of MFIs and their clients has increased greatly during the period under study. The use of the PR-RT model is justified for the study of competition in microfinance since the PR model depends on the firm-level data, it is robust to the geographical definition of the market and it allows using cross-country data with diversified ownership patterns (Mersland and Strom, 2012). We describe the competitive behaviour of MFIs of the above countries using comparative static properties of reduced-form revenue equations. Both static and dynamic panel data models have been used. Results show that the microfinance markets in India and Indonesia can be both monopolistic and monopolistically competitive. In Philippines and Ecuador microfinance markets generally operate under conditions of monopoly, whereas Peru's microfinance market is generally monopolistically competitive.

The study contributes to the literature at many levels. First, the analysis provides a cross-country investigation of the implications of differing levels of competition as measured by the Panzar and Rosse (1987) H-Statistics. Second, the study focuses this investigation on five countries with vibrant microfinance markets using country-level panel datasets. Third, it contributes methodologically, by measuring financial fragility through dynamic panel data estimations. The dynamic approach takes care of the dynamic and reforming market landscapes and regulatory environment of the microfinance industries under scrutiny.

[2] For a detailed literature review on the assessment of competitive behaviour in banking see, for example, Turk-Ariss (2009) and Leuvensteijn et al. (2011).

The remainder of the paper is organized as follows. Section 2 provides a brief review of relevant literature basically to explain the theoretical contexts of the PR-RT. A detailed exposition of the methodologies and the empirical specifications of the models are given in Section 3. Section 4 provides data overview and summary statistics. Results are reported in Section 5. Section 6 presents the concluding remarks.

2. Measuring Competition

Studying industry level competitive conditions is common in industrial organization literature and several studies have focused on the level of competition in banking at country and region-level aggregations. There are two main streams in this literature: studies that adopt a structural or informal approach and those that follow a non-structural or a formal approach. The structural method, originates from the industrial organisation theory, and uses the number of banks or the degree of banking industry concentration as a proxy for market power. For instance, n-firm concentration ratios and the Herfindahl-Hirschman index (HHI). This approach mainly follows the structure-conduct-performance (SCP) paradigm (i.e., the market structure has a direct influence on firms' economic conduct that finally affects their market performance)[3] and the competing efficiency hypothesis (i.e., more market concentration reflects efficient firms' market share gains). The SCP hypothesis states that larger and smaller number of firms can fix prices easily and hence, are more likely to be engaged in monopolistic behaviour. While the latter hypothesis suggests that the positive links, between concentration and profits are caused by both anticompetitive behaviour and higher operating efficiency of larger businesses (Turk-Ariss, 2009).

The structural approach has several deficiencies (Hannan, 1991). Even though these hypotheses have been frequently employed in the empirical research, they are not always supported by standard microeconomic theory (Delis et al., 2008). More recently the non-structural approaches[4] have been increasingly used to draw inferences on firms' observed behaviour from the estimated parameters of equations derived from theoretical models of price and output determination (Lau, 1982; Bresnahan, 1982; Panzar and Rosse, 1987; Berger et al., 2004; Carbo et al., 2009). For instance, the PR-RT examines the relationship between price variations and the revenue of the firm to see whether firm-

[3] This is also called SCP collusion hypothesis. To discuss the SCP literature in detail, however, is beyond the scope of this paper.
[4] It is also known as the new empirical industrial organization (NEIO) models.

level conduct is in accordance with the textbook models of perfect competition, monopolistic competition, or monopoly. The standard procedure for the estimation of H-statistic involves the fixed effects (FE) estimations of firm-level panel data. The correct identification of the H-statistic relies upon an assumption that markets are in long-run equilibrium at each point in time when the data are observed (Goddard and Wilson, 2009).

Together, demand, costs and conduct determine the equilibrium price and quantity according to the PR model. Thus, applying the PR-RT to microfinance data assesses competitive conditions in the industry and relies on the premise that MFIs apply different pricing strategies as input costs change depending on the market structure they operate in. Therefore, whether an MFI operates in a competitive market or exercises some monopoly power may be inferred from the analysis of that MFI's total revenue as it corresponds to changing input prices. Accordingly, all determinants of costs and demand—particularly factor prices—must be included in revenue functions while applying the PR-RT. Let the marginal revenue (MR) and marginal cost (MC) functions of MFI *i* be defined as:

$$MR = R'_i (x_i, n, z_i) \quad (1)$$

$$MC = C'_i (x_i, w_i, t_i) \quad (2)$$

where, R'_i is the marginal revenue (MR) function, C'_i is the marginal cost (MC) function, x_i represents outputs, z_i and t_i consist of exogenous variables that shift the revenue and cost functions respectively, w_i is a vector of m factor input prices and n is the number of MFIs in the market.

Profits are maximized where MFIs' MR = MC. Therefore,

$$R'_i (x_i, n, z_i) - C'_i (x_i, w_i, t_i) = 0 \quad (3)$$

At a market level equilibrium under perfect competition, the zero-profit constraint must also hold. Hence,

$$R^* (x^*, n^*, z) - C^* (x^*, w, t) = 0 \quad (4)$$

Based on the above conditions, the PR model provides a measure of the degree of competitiveness, the 'H-statistic', which ranges from minus infinity to unity (de Rozas, 2007). The H-statistics are

then calculated from the comparative statics properties of a reduced form revenue equation, which measures the sum of the elasticities of the total revenue R of the MFI with respect to the MFI's n factor input prices W_i as follows (Gischer and Stiele, 2008)[5]:

$$H = \sum_{i=1}^{n} \frac{\partial R}{\partial W_i} * \frac{W_i}{R} \qquad (5)$$

In this case, the change in factor input prices represents the equilibrium revenues earned by MFI *i*.

3. Model Specification and Estimation

The country-level H-statistics are estimated by the standard reduced-form specification on the panel data for each country as follows:

$$\ln TR_{it} = \alpha + \beta_1 \ln(W_{L,it}) + \beta_2 \ln(W_{F,it}) + \beta_3 \ln(W_{K,it}) + \gamma_1 \ln(Y_{1,it}) + \gamma_2 \ln(Y_{2,it}) + \gamma_3 \ln(Y_{3,it}) + u_i + \varepsilon_{it} \qquad (6)$$

where the subscripts *i* and *t* refer to MFI *i* operating at time *t*. The dependent variable TR_{it} indicates total revenue defined as the financial revenues net of financial and operating expenses, impairment losses and taxes. Financial revenue of an MFI includes all interest, fees and commissions incurred on the loan portfolio and other financial assets. This amount also includes other revenues related to the provision of financial services[6]. Bikker et al. (2009) note that the Panzar-Rosse price function, or the scaled revenue equation cannot be used to infer the degree of competition and that only an unscaled revenue equation yields a valid measure for competitive conduct. So, the current study uses this as the dependent variable which is an unscaled measure of total revenue. The set of explanatory variables include three factor input prices: $W_{L,it}$ (price of labour) is represented by the ratio of personnel expenses to total assets (*pea*), $W_{F,it}$ (price of funds) is represented by the ratio of interest expenses to total assets (*fea*) and $W_{K,it}$ (price of physical capital) is defined as the ratio of administrative expenses to total assets (*aea*)[7]. $Y_{1,it}$ and $Y_{2,it}$ represent capitalisation and risk scenarios of MFIs proxied by the equity-to-assets (or capital-assets-ratio) ratio (*car*) and the loans-

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[5] The formal derivation of the H-statistic can be found in Panzar and Rosse (1987).

[6] For further details, see: http://www.mixmarket.org/fr/about/faqs/glossary#ixzz2anfY8d74

[7] The study basically follows Turk-Ariss (2009) and Delis et al. (2008) to construct these proxies. However, all proxies were not the most precise ones. For example, the ratio between labour costs and the number of employees was a better proxy for 'price of labour'. However, as the MIX database lacks suitable and sufficient observations on the number of personnel, we used the next best proxy: the ratio of personnel expenses to assets. For 'price of funds', interest expenses include all interest, fees and commissions incurred on all liabilities, including deposit accounts of clients held by the MFI, borrowings, subordinated debt and other liabilities.

to-assets ratio (*glpta*) respectively. These two explanatory variables reflect the differences in the capital structure and the loan risk of sampled MFIs and control for their business and portfolio mix. It is expected that better capitalization levels and a higher allocation of assets to loans will generate more revenues and therefore are positively associated to the dependent variable. To control for potential effects of size across MFIs, we include $Y_{3,it}$ which is the natural logarithm of total assets. While there is no expectation about the sign on total assets, the results of the estimation would provide information on whether the MFIs face economies or diseconomies of scale. The variable definitions are provided in Table 2.

A critical feature of the H-statistic is that the test must be undertaken on observations that are in long-run equilibrium at each point in time. Since the competitive capital markets will equalize the risk-adjusted rate of return across MFIs, the rate of return should not be correlated statistically with input prices in equilibrium. Therefore, as suggested by Shaffer (1982), the long-run E-statistic is calculated to test for equilibrium using 'return on assets' (ROA) as the dependent variable instead of the total revenue. The selection of ROA is again justified as it is a widely used financial performance indicator in the microfinance literature. In this context, E = 0 indicates the equilibrium situation. The reason is that market forces should equalise ROA across firms, so the level of ROA is not linked with input prices. Thus, in the PR framework, banks should be observed from a long-run equilibrium perspective and in line with previous research, the problem of volatile economic environment in the countries of study is overcome by considering a panel data specification and testing the observations for long-run equilibrium using the following model:

$$\ln(1 + ROA_{it}) = \alpha + \beta_1 \ln(W_{L,it}) + \beta_2 \ln(W_{F,it}) + \beta_3 \ln(W_{K,it}) + \gamma_1 \ln(Y_{1,it}) + \gamma_2 \ln(Y_{2,it}) + \gamma_3 \ln(Y_{3,it}) + u_i + \varepsilon_{it} \quad (7)$$

where ROA is the return on assets less taxes. A constant (one) is added to ROA to avoid taking the natural logarithm of a negative number and this significantly increases the number of observations used in the regressions. The equilibrium E-statistic is calculated as the sum of the input price elasticities. The hypothesis E = 0 is tested and if rejected, the market is not in equilibrium, intuitively indicating that in the long-run ROA is not related to input prices.

MFI-level fixed effects (FE) are most likely to capture the differences in individual data as MFI-level and country-level yearly data have been used. So, we opted for FE models. Also, most researchers previously have implemented the PR-RT for banking data through FE estimation of (1)

and (2) above. However, estimations of one-way static fixed effects models of this type sometimes may cause grossly misleading inferences, particularly in the ‘small T, large N’ (smaller number of time identifiers and larger number of firms) data context. Again, we need to assume that the product market is in long-run equilibrium, but if this assumption is not met results do not hold. So, we need to opt for a dynamic version of this relationship at least for three reasons. First, the competitive paradigm by definition makes clear dynamic predictions as firms basically fight for profits: strong players pass the market test and continue, while weak performers exit or shrink (Goddard and Wilson, 2009). Second, from time-series econometrics viewpoint, if total revenues in the current year are actually linked with those of the previous year(s) then model misspecifications potentially result in a pattern of autocorrelation in the error terms and clearly with auto-correlated disturbances in “small T, large N” panels (smaller number of time identifiers and larger number of firms) (typical in the empirical banking literature), the fixed and random effects estimators are biased toward zero, potentially creating misleading inferences on the nature or intensity of competition. Third, as Delis et al. (2008) notes, accommodation of new input prices is not instantaneous, but partial, and therefore, a dynamic estimation of the relationship can give better estimates of market power.

Hence, dynamic modelling is vitally important and for that reason, we additionally introduce the dynamic version of model (1) and (2) within a dynamic panel data (DPD) context. We were motivated for applying this approach mainly because of DPD’s statistical importance of accounting for short-run dynamics in the data. DPD modelling potentially solves the inference limitations associated with data non-stationarity as well (which is a common problem of the time series dimension of panel data). Besides, and arguably most importantly, unlike a static model, a DPD model can take care of the changes occurred over time in sampled countries’ market landscapes and regulatory environments. The dynamic extension of model (1) is linear in the parameters and following Delis et al. (2008), we specify an autoregressive-distributed lag model in the following form:

$$\begin{aligned} \ln TR_{it} = {} & \alpha' + \beta_{l0} \ln TR_{i,(t-1)} + \beta'_1 \ln(W'_{L,it}) + \beta'_{11} \ln(W'_{L,i(t-1)}) + \beta'_2 \ln(W'_{F,it}) + \beta'_{21} \ln(W'_{F,i(t-1)}) + \\ & \beta'_3 \ln(W'_{K,it}) + \beta'_{31} \ln(W'_{K,i(t-1)}) + \gamma'_1 \ln(Y'_{1,it}) + \gamma'_{11} \ln(Y'_{1,i(t-1)}) + \gamma'_2 \ln(Y'_{2,it}) + \\ & \gamma'_{21} \ln(Y'_{2,i(t-1)}) + \gamma'_3 \ln(Y'_{3,it}) + \gamma'_{31} \ln(Y'_{3,i(t-1)}) + u_i + \varepsilon_{it} \qquad (8) \end{aligned}$$

where $(t-1)$ is the one-period time lag, u_i are the individual effects and ε_{it} is the idiosyncratic disturbance. For the set of explanatory variables, x, we assume that $E(\varepsilon_{it} \mid x_{it}, u_i) = 0$, which implies

that there is no possibility of feedback from lagged revenue to current x values. Thus, as in the static case, the H-statistic is obtained by $H' = \beta'_1 + \beta'_2 + \beta'_3$.

As described earlier, we also test the observations for long-run equilibrium using the following model:

$$\ln(1 + ROA_{it}) = \alpha' + \beta_{l0} \ln TR_{i,(t-1)} + \beta'_1 \ln(W'_{L,it}) + \beta'_{11} \ln(W'_{L,i(t-1)}) + \beta'_2 \ln(W'_{F,it}) + \beta'_{21} \ln(W'_{F,i(t-1)}) + \beta'_3 \ln(W'_{K,it}) + \beta'_{31} \ln(W'_{K,i(t-1)}) + \gamma'_1 \ln(Y'_{1,it}) + \gamma'_{11} \ln(Y'_{1,i(t-1)}) + \gamma'_2 \ln(Y'_{2,it}) + \gamma'_{21} \ln(Y'_{2,i(t-1)}) + \gamma'_3 \ln(Y'_{3,it}) + \gamma'_{31} \ln(Y'_{3,i(t-1)}) + u_i + \varepsilon_{it} \quad (9)$$

where ROA is the return on assets less taxes and the other variables are the same as defined earlier.

As MFI-level fixed effects (FE) are most likely to capture the differences in individual data, estimations through the FE and random effects (RE) models of (6) and (7) are reasonable. However, an additional difficulty is that total revenue and capital-assets-ratio can be simultaneously determined by managerial competence or aptitude that cannot always be observed[8]. Again, ROA is determined by financial revenue which consists of interest rate and fees components. We also have the endogeniety problem as both capital-assets-ratio and ROA are scaled by a common factor, total assets. In this case, the endogeneity comes from an uncontrolled confounding variable—interest and fees—as it is an extraneous variable which correlates with both the dependent variable and the independent variable. To overcome these problems we employ the instrumental variables (IV) estimations. We instrument through lagged explanatory variables as suggested by Deaton (1995). The independent variables are all simultaneous and, therefore, the lagged variables are not related to the dependent variables. Since, the number of instruments (L) is greater than the number of regressors (K) we have a set of over-identifying restrictions. The instruments' independence of the error term is tested with Hansen's (1982) J-test. A high p-value (a low value of χ^2) indicates that the instruments and the error terms are uncorrelated, and therefore, the endogeneity problem no longer persists[9].

The MFI-individual effect may also suffer from unobserved firm heterogeneity (such as, managerial capabilities) due to the diversified characteristics of the sampled MFIs. We, therefore, employ the Hausman test to check if the unique errors (u_i) are correlated with the regressors and decide whether to use a FE or RE model. If the Hausman test indicates that the chi-squared values are significant

[8] For a detailed discussion on the endogeneity between the capital-assets-ratio and total revenue see, for instance, in Delis et al. (2008).

[9] These primarily apply for the static panel data estimations.

we should opt for using the FE models. To deal with the endogeneity problem, we estimate the fixed-effects two-stage least squares (FE2SLS) estimator in addition to the error components two-stage least squares (EC2SLS of Baltagi, 1981).Then, following Baltagi (2006), Hausman tests based on the difference between FE2SLS and EC2SLS were applied and depending on whether the χ^2 values were significant or insignificant FE2SLS or EC2SLS model estimates have been reported.

The "system GMM" estimator is employed to estimate the model, which is the augmented version of Arellano-Bond (1991). The "system GMM" estimator sets up the model as a system of equations, one for each time period, where the instruments—created from the lagged values—applicable to each equation differ. Thus, equation (8) and (9) have been estimated using the two-step system GMM method proposed by Blundell and Bond (1998)[10] with Windmeijer's (2005) finite-sample correction for the two-step covariance matrix. Following Delis et al. (2008), variable capital-assets-ratio is used as an endogenous variable. Then, as suggested by Bond (2002), the endogenous variable (*i.e.,* capital-assets-ratio) is instrumented following 'GMM style' symmetrically to the dependent variable (unscaled total revenue) with an autoregressive error term similar to the static case.

Panzar and Rosse (1989) note that based on the reduced-form revenue equation the H-statistics can be written as:

$$H = \beta_1 + \beta_2 + \beta_3 \qquad (10)$$

Equation (6) in essence indicates that H is the sum of elasticities of the reduced form revenue with respect to all the factor prices. Explicitly, the statistic measures the percentage change in an MFI's equilibrium revenue caused by a 1 per cent change in all of the MFI's input prices. As a result, although information on costs is not required, the computation of the H statistic requires firm-specific data on revenues and factor prices. This method is a simple, transparent and valuable tool in assessing market conditions. Also, by utilizing MFI-level data, this approach allows for MFI-specific differences in the production function. As revenue data are easy to observe compared to output prices, data availability should not be a constraint. Bikker and Haaf (2000) note that the PR

[10]The original Arellano-Bond "difference GMM" model transforms the regressors by differencing and uses the generalized method of moments (Hansen, 1982). A potential weakness of this estimator was revealed in later works by Arellano and Bover (1995) and Blundell and Bond (1998). The lagged levels are often rather poor instruments for first differenced variables, especially if the variables are close to a random walk. Their modification of the estimator includes lagged levels as well as lagged differences.

approach basically includes four conditions: (1) firms are operating at their long-run equilibrium, (2) performance of the firm is influenced by the actions of other firms' in the market, (3) the cost structure is homogeneous and, (4) the price elasticity of demand is greater than unity. By not requiring a locational market definition a priori, the PR framework avoids the potential bias caused by the misspecification of the market boundaries; hence, the H-statistic will reflect the average of an MFI's conduct in each market when that MFI operates in more than one market. Another important feature of the PR approach is that it does not require observations on all firms in a market. PR H-statistic is a direct measure of competitiveness that takes into account potential, direct or indirect competitive effects. Thus, applying this method allows us to even examine the competitive behaviour of a single firm (Gischer and Stiele, 2008).

Assuming profit maximization, Panzar and Rosse (1987) depicts that in a collusive environment an increase in input prices will increase MC and reduce equilibrium output and revenues. As Table 1 summarises, H is negative ($H \leq 0$) either for a monopoly or for an oligopoly (perfectly colluding oligopoly and a homogeneous-conjectural-variations oligopoly). H equals unity ($H=1$) under perfect competition as an increase in input prices will increase MC and MR by the same amount. H ranges between 0 and 1 ($0 < H < 1$) under monopolistic competition where an increase in input prices lead to a less than proportional increase in revenues due to inelastic demand faced by the individual MFI. Panzar and Rosse (1987) further note that, from an econometric standpoint, the rejection of $H \leq 0$ rules out the monopoly model; the rejection of $H \leq 1$ excludes all the three models; and the rejection of both $H \leq 0$ and the $H = 1$ hypothesis (but not the $H \leq 1$ hypothesis) implies that only monopolistic competition model is consistent with the data.Refer to Bikker et al. (2009), for a detailed discussion on the interpretations of the H-statistic.

4. Data

Required MFI-level data were collected from the MIX Market database[11]. The MIX Market uses 'diamonds' to rank MFI-data where a rank of the highest of 5-diamonds means the best quality[12]. Our sample contains MFIs which have at least a 3-diamonds ranking: 5-diamonds (27.59%), 4-diamonds (30.46%) and 3-diamonds (40.62%). After making adjustments for missing values the study finally employs static and dynamic models to test the degree of competitiveness in the vibrant microfinance industries of India, Indonesia, Philippines, Peru and Ecuador covering a period of 15

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

[12] The level of disclosure for each MFI is indicated through a "diamond" system: the higher the number of diamonds, the higher the level of disclosure.

years—1996 to 2010. These countries have distinctive characteristics in the liberalization and regulation of MFIs functioning within the country.[13] Five separate panel datasets have been created corresponding to the microfinance sectors in each of these countries. The data are unbalanced as all MFIs included in the database do not have equal number of observations for every year.

These countries were selected for a number of reasons. First, the study attempts to cover regional differences in the level of competition and differences in regulatory frameworks. The revenue streams of MFIs may vary depending on their product portfolio mix. Employing the PR-RT, we can compare the revenue stream of a 'micro-saving' centric country (Indonesia) with that of a 'microloan' centric country (India) as the country-specific revenue sources do not matter much. Second, selected countries also reflect a portfolio of countries where the microfinance sectors are getting increasingly competitive and characterized by differing levels of concentration. For instance, the Herfindahl-Hirschman index (HHI) for India ranges from a high of 111 in 2004 to a low of 89 in 2010. Indonesian microfinance sector is more concentrated, with an HHI of 301 in 2010, up from 90 in 2004, exhibiting much higher concentration level than the average of EAP region countries (41 in 2004 and 56 in 2010). The concentration level of the microfinance industry in Philippines is also increased in 2010 (an HHI of 41 in 2004 to 56 in 2010). Concentration levels of the microfinance sectors in Peru and Ecuador, however, have decreased in 2010. Thus, by including these five countries in the databases, the study covers microfinance markets of both high (Indonesia and Philippines) and low (India, Peru and Ecuador) concentrations.

Third, these countries have varying magnitudes of population, GDP and footprint of the microfinance sectors[14].

After applying the filtering rules the final sample covers a total of 342 MFIs: India (106 MFIs), Indonesia (45 MFIs), Philippines (79 MFIs), Peru (62 MFIs) and Ecuador (50 MFIs). The static models estimated in the analysis utilized data for the whole sample period—1996 to 2010.

[13] Another country with significant history and vibrant presence of microfinance activities, Bangladesh, is excluded from the sample due mainly to non-availability of sufficient number of observations on selected MFIs that can handle statistical tests and dynamic panel data estimations as applied in this exercise.

[14] India is one of the biggest countries in the world, with a population of around 1.27 billion in 2013, as well as a country boasting several big MFIs in the world. On the contrary, for instance, Ecuador and Peru are much smaller than India having only 15.4 million and 30.4 million in population respectively. Philippines (97.7 million) and Indonesia (250 million) are two other sampled countries which have quite a high population in comparison with Ecuador and Peru. These countries also vary in terms of their magnitudes of GDP per capita. For example, per capita GDP in Peru was 6,796 US dollars in 2012, the highest, whereas in that year India's per capita GDP was the lowest among these countries, only 1,489 US dollars. Per capita GDP of Indonesia, Philippines and Ecuador, however, were 3,557 USD, 2,587 USD and 5,425 USD respectively.

However, the dynamic models have been estimated for the period 2005-2009 as a longer time period resulted in the problem of too many instruments and a large collection of instruments can over-fit endogenous variables causing a loss of observations (Roodman, 2009). The sample contains MFIs of different maturity level (new, young and matured) and types like NGO, non-bank financial institution, bank and credit union.

5. Discussion of Results

The reduced-form revenue functions stated in equations (6) – (9) are all linear in their unknown parameters. So, the models are appropriate for estimation utilizing standard methods.

5.1 Descriptive Statistics

Descriptive statistics of the variables included in the analysis for the period 2004–2009 are provided in Table 3. In terms of the number of MFIs and observations, India and Philippines top the list of the sampled countries in the sample followed by Peru, Ecuador and Indonesia. However, Peru and Ecuador have the highest average total assets over the period 2004-2009 and India, Philippines and Indonesia are after them. MFIs in the Latin American countries of Peru and Ecuador have achieved the highest average profitability over the sampled period under scrutiny, with an average ROA of 3.3% and 2.2% respectively. The East Asian countries in the sample—Indonesia and Philippines—have earned a moderate ROA over this period: 1.6% and 1.9% respectively. India has the lowest profitability rate, only 0.4%. In terms of interest incomes, India is the best performer followed by Peru, Ecuador, Philippines and Indonesia.

5.2 Static revenue tests

As a standard procedure for estimating the H-statistics we apply the fixed effects (FE) and random effects (RE) regression with the 2SLS technique on the static version of our estimation model in equation (6), commonly known as Panzar-Rosse static revenue tests, and results are presented in Table 4. The coefficients on the proxies used for the unit price of funds (fea (W_F): ratio of interest expenses to intermediated funds), unit price of physical capital (aea (W_K): ratio of administrative expenses to fixed assets) and unit price of labour (pea (W_L): ratio of personnel expenses to total assets) are generally negative, but statistically significant only in models for the MFIs in two sampled Latin American countries—Peru and Ecuador. These positive significant coefficients generally suggest sufficient stability of the equations. Negative coefficients, though statistically insignificant, of the input price variables in India, Indonesia and Philippines provide evidence of excess capacity in these microfinance industries. Positive and generally significant coefficients of

the loans-to-assets variable and highly significant positive coefficients of the size variable (in logs) confirm positive effects of loan and scale (economies of scale). The capitalization (equity-to-assets) variable is generally statistically insignificant. However, the positive significant coefficient of the equity-to-assets variable for the MFIs in Ecuador indicates that improved capitalization may raise revenues, which is quite similar to theoretical predictions.

Table 4 further shows that the values of the PR H-statistics are negative and statistically significant only for the MFIs in Indonesia and Peru. Wald tests for the hypotheses of H = 0 (monopoly) and H = 1 (perfect competition) are both rejected at 5% level in these two models as well. Therefore, the dominant market form in Indonesia and Peru is monopolistic competition. Again, a closer look at the results on India, Philippines and Ecuador demonstrate that the tests of hypotheses fail to reject a monopolistic environment in these countries' MFI industries. However, this is not quite straightforward. As Bikker et al. (2009) explain, a negative H-statistic may also arise under the conditions of long-run competition with constant average cost and short-run competition. Thus, we may have to examine other scenarios including individual cost structures, for instance. We test for the long-run equilibrium estimating equation (8) using ROA as the dependent variable and the results are reported in Table 5. The Wald tests performed always fail to reject the hypothesis of equilibrium (E = 0), which quite convincingly indicates that our analysis is well specified.

5.3 Dynamic revenue tests

Table 6 reports the estimation results of equation (9) and shows the H-statistics for each of the countries in the sample signifying the dynamic revenue tests. The dependent variable, total revenue in natural logs, is negatively linked with the input prices—W_F, W_L and W_K—with only one exception: price of labour (W_L) in Indonesia. These negative coefficients essentially suggest that increased factor costs lead to lower revenue. This could also indicate cost cutting efforts by MFIs. However, the coefficients on input prices are statistically insignificant, excepting price of labour (W_L) in India and price of loanable funds (W_F) in Indonesia. Major contributors to the H-statistics vary from country to country. For instance, in India, Peru and Ecuador, price of labour (W_L) contributes more to the H-statistic, while in Indonesia and Philippines price of loanable funds (W_F) and price of capital (W_K) are the major contributors respectively. Contributions of some of the input price coefficients are sometimes negligible. For example, overall impact of price of capital (W_K) in India on the factor price elasticity is negligible. This result is in line with previous banking studies (see, for instance, Turk-Ariss, 2009; de Rozas, 2007). However, as the coefficients are statistically insignificant the overall evidence is unclear. As expected, the coefficients of the equity-to-assets

ratio are all positive and generally highly significant in India and Philippines. Positive significant coefficients on the equity-to-assets variable indicate that the protected capital buffers encourage risk-taking and that the well-capitalized MFIs are not involved in riskier operations. Also, the reason might be the absence of regulatory pressures so that riskier banks are allowed to carry more equity. Therefore, higher capital ratio will generate higher revenues and MFIs are likely to improve their earning capability through riskier loan portfolios. Reported positive significant coefficient for the loans-to-assets variable seems plausible as more loans potentially reflect more income. The sign on log of size variable is also positive and mostly highly significant, which clearly indicate that the MFIs under survey generally encounter economies of scale. These results are similar to what we have already found in the static revenue tests above and indicate the robustness of our results.

Wald tests (F-statistics) were conducted to test whether or not the calculated H-statistics are statistically different from zero and unity. A closer look at the results of the dynamic revenue tests suggests that the calculated PR H-statistics vary from country to country. Also, the results in terms of market structure are dissimilar to their static counterpart in some cases. For instance, tests of hypotheses of $H \leq 0$ (monopoly) and $H = 1$ (perfect competition) are both rejected at 5% level for the MFIs in India and Peru suggesting that total revenues of the MFIs in these countries appear to be earned under conditions of monopolistic competition and any form of conjectural variation oligopoly and monopoly can be ruled out during the sample period. Again, the results of Indonesia, Philippines and Ecuador show that the tests of hypotheses fail to reject a monopolistic environment in these countries' MFI industries. Negative H-statistic may arise under many situations. We have negative H-statistics for the MFIs in all countries in the sample require acareful discussion on the results and an examination of other scenarios including individual cost structures etc. (Bikker et. al, 2009).

In order to validate the above test results, the long-run equilibrium condition has to be met. In other words, the microfinance industries in the countries under study should be in long-run equilibrium during the sampled period. Table 7 presents the equilibrium positions in the microfinance industries by estimating equation (10) with ROA as the dependent variable. The Wald tests fail to reject the null hypothesis $E = 0$ at 5% level for all countries leading us to conclude that the microfinance industries were in the long-run equilibrium over the period 2005-2009. The tests for long run equilibrium produce E-statistics which are close to zero and are further supported by the Wald tests confirming that the long term equilibrium criterion has been met.

Thus, overall predictions regarding the market structures of the countries under scrutiny are not all the same in dynamic specifications. Notably, the static model suggests that the MFIs in India earn total revenue under a condition where monopolistic environment cannot be ruled out. Whereas the dynamic model suggests that the dominant market form in India is monopolistic competition. Thus we see that the dynamic model provides a lower estimate of market power. In case of Indonesia, however, the dynamic specification suggests a monopoly nature of the market although its static version suggested that MFIs in this country were operating under the condition of monopolistic competition to earn their total revenue. So, the dynamic specification suggests a higher estimate of the market power. In cases of Philippines, Peru and Ecuador, however, both the static and dynamic model specifications deliver similar results: both in static and dynamic models, MFIs in Philippines and Ecuador always operate under the condition of monopoly while MFIs in Peru earn their total revenue under the condition of monopolistic competition.

Notably, a monopolistic competition structure allows for product differentiation. Microfinance sectors in the sampled countries are traditionally highly concentrated markets. MFIs tend to differ with respect to product quality and advertising, although their core business is fairly homogeneous. Countries with monopolistically competitive market structures are not generally characterized either as a monopoly or conjectural variations short-term oligopoly. The empirical findings reveal that market power resulting from high concentration levels does not exclude competitive behaviour. This suggests that other factors may account for differences in the degree of competition in the microfinance industries under scrutiny. Another very important finding of the study, mainly from the econometric point of view, is that it does not really matter whether we use any static model or a dynamic model specification at least for Philippines, Peru and Ecuador. Results are generally consistent irrespective of the model we employ. This further confirms the validity of the methodology we apply and acts as an additional tool for robustness check.

6. Conclusions

Competition in the microfinance industry is important to the broader development agenda. Increased competition is expected to result in greater benefits in terms of better access to credit with lower interest rates. This may not always be the case in the microfinance industry and in fact, previous studies have suggested that competitive microfinance markets might cause the markets to fail. One plausible reason is that without information-sharing borrowers may lack the discipline to repay in a competitive set-up. However, only a few studies have attempted to determine the extent of competition in the microfinance industries. This study applies the Panzar-Rosse revenue tests

(PR-RT) to get the H-statistics to account for the intensity of competition in five vibrant microfinance industries: India, Indonesia, Philippines, Ecuador and Peru. The analysis further distinguishes between static and dynamic versions of the reduced-form models used in estimations to substantiate whether predictions regarding the market structure remain unchanged. The resulting specifications have been tested for panel data from the microfinance industries of the above mentioned countries spanning the period 1996-2010. Distinct characteristics and differing market concentrations in these countries make the regional comparison of results easier.

Static and dynamic models estimated for the MFIs in Philippines, Peru and Ecuador deliver consistent results which show that the intensity of market competition remains the same. Similar estimations for India and Indonesia show that microfinance markets in these countries can be described as monopolistic or monopolistically competitive. This clearly suggests that the concentration levels are differing (from high to low) in the sampled microfinance markets. However, there are scopes for making these markets more competitive by creating more conducive atmosphere for the participation of other MFIs and reducing unnecessary restrictions on their activities. Promoting competition may not improve the incumbent socially-motivated MFI's financial sustainability and outreach performance, and may in fact result in mission drift concerns. Besides, as discussed above, a competitive microfinance industry cannot guarantee better performance of an MFI, whereas monopoly of an altruistic MFI can be good for their clients. Owing to competitive pressures, MFIs cannot always pass on increase in input prices to their clients. So, achieving financial sustainability and balancing it with higher outreach continues to be an ongoing challenge for MFIs as of now and they really need to improve their efficiency by reducing costs. Our results also suggest that the static models do tend to underestimate or overestimate the market power in India and Indonesia as the static and dynamic models give dissimilar results. This result in a way confirms the results of Delis et al. (2008) and can be viewed as the strength of the study.

These results have significant implications for researchers and policy makers. Although some of the markets seem relatively oligopolistic or monopolistic, our results confirm that there are strong signs of competition. However, further research can contribute to the existing knowledge in a number of ways. Researchers could bring about further evidence applying new data and checking the results with new models. Also, the aggregation of sampled MFIs can be based on different loan methods, legal types and regulatory regimes. It is also reasonable to account for the critiques of the new empirical industrial organisation (NEIO) literature as we have employed the PR-RT in this exercise. There is also a need to investigate the impact of the depth of outreach on the revenues and

lending rates of MFIs. This would be particularly crucial in understanding if greater competition in microfinance industry leads to mission drift. At a broader level of analysis this study underlines the relevance of more appropriate empirical methods to characterise potentially collusive behaviour in different microfinance markets.

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Table 1: Interpreting the Panzar-Rosse H-statistic

Parameter region	Competitive environment test
$H \leq 0$	-Monopoly or conjectural variations short-term oligopoly -Each MFI operates independently as under monopoly profit maximising conditions -H is a decreasing function of the perceived demand elasticity
$0 < H < 1$	-Monopolistic competition -Free entry (Chamberlinian) equilibrium excess capacity -H is an increasing function of the perceived demand elasticity
$H = 1$	-Perfect competition, natural monopoly in a perfect contestable market, or sales maximising firm subject to break-even constraint -Free entry equilibrium with full (efficient) capacity utilisation

Parameter region	Market equilibrium test
$H = 0$	Equilibrium
$H \leq 0$	Disequilibrium

Source: Molyneux et al. (1996).

Table 2: Description and definition of variables

Variable name	Description
Interest income	Interests and revenues scaled by (assimilated over) total assets
Unit price of labour (pea)	Ratio of personnel expenses to total assets. Personnel expenses include wages and salaries, social security contributions, contributions to pension funds, and other staff-related expenses. *Source:* Author's calculations using the MFI-level yearly financial data from the MIX
Unit price of funds (fea)	Ratio of interest expenses to total assets (current accounts, savings accounts, time deposits, repurchase agreements, as well as alternative funding sources such as retail bonds). *Source:* The yearly MIX data
Unit price of physical capital (aea)	Ratio of administrative expenses to total assets. Administrative expenses include rents, service charges, security, information systems and communications, other office and insurance expenses, professional charges, publicity and advertising, and depreciation. *Source:* The yearly MIX data
Size	Natural logarithm of total assets *Source:* Author's calculations using the MFI-level yearly financial data from the MIX
Capitalization (car)	Ratio of equity (capital) to total assets *Source:* The yearly MIX data
Loans (glpta)	Ratio of (gross) loans to total assets *Source:* Author's calculations using the MFI-level yearly financial data from the MIX

Table 3: Summary/Descriptive statistics for the sampled MFIs over the period 2004-2009

	No. of MFIs	Observations	Statistic	Assets	Loans	Equity	ROA	Interest Income
India	106	453	Mean	24.407	20.786	3.774	0.004	1.079
			S.D.	78.972	74.814	14.839	0.107	4.935
			Minimum	0.000	0.000	-0.397	-1.013	-7.152
			Maximum	897.871	960.794	213.038	0.563	58.188
Indonesia	45	191	Mean	8.099	6.277	2.300	0.016	0.275
			S.D.	52.272	40.622	17.041	0.105	2.114
			Minimum	0.001	0.001	0.000	-0.560	-0.434
			Maximum	529.796	397.100	169.631	0.145	27.073
Philippines	79	379	Mean	8.965	5.962	1.696	0.019	0.285
			S.D.	12.296	8.294	2.211	0.080	0.575
			Minimum	0.075	0.024	-0.227	-0.583	-1.076
			Maximum	81.916	55.827	15.814	0.229	4.182
Peru	62	314	Mean	67.193	54.194	10.466	0.033	2.577
			S.D.	137.802	112.773	16.446	0.063	4.991
			Minimum	0.246	0.165	-0.011	-0.337	-5.448
			Maximum	1278.721	1040.561	111.594	0.164	35.932
Ecuador	50	245	Mean	27.233	21.549	3.831	0.022	0.368
			S.D.	63.692	49.841	7.063	0.044	0.743
			Minimum	0.091	0.078	0.015	-0.232	-0.710
			Maximum	341.106	253.682	41.217	0.161	4.962

Note: Excepting ROA, statistics figures are in million US$. Author's calculations based on MIX data collected from www.themix.org. ROA figures are in percentages.

Table 4: Static Revenue Test (Panzar-Rosse H-statistics of sampled MFIs in selected countries)

	India	Indonesia	Philippines	Peru	Ecuador
log(car)	0.329	-1.720	0.530	-1.334	0.905***
	(0.190)	(1.331)	(0.294)	(1.573)	(0.186)
log(fea)	-0.040	-0.194	0.062	-0.608*	-0.135
	(0.288)	(0.200)	(0.163)	(0.252)	(0.089)
log(pea)	-0.205	-0.336	0.229	-0.266	0.642**
	(0.142)	(0.354)	(0.197)	(0.678)	(0.224)
log(aea)	0.111	-0.418	-0.087	-1.070**	-0.419*
	(0.144)	(0.269)	(0.241)	(0.349)	(0.212)
log(glpta)	1.583***	2.978*	0.794*	2.510	0.671
	(0.450)	(1.317)	(0.403)	(1.754)	(0.457)
lsize	17.953***	24.388***	15.986***	8.273	19.000***
	(1.373)	(5.063)	(2.203)	(4.892)	(1.251)
Constant	-37.250***	-58.858***	-30.387***	-16.841	-38.978***
	(4.190)	(15.734)	(5.960)	(12.865)	(3.338)
PR H-statistic	-0.134	-0.948*	0.203	-1.944**	0.088
	(0.292)	(0.481)	(0.217)	(0.709)	(0.191)
Monopoly H=0	0.21	3.90	0.87	7.52**	0.21
P-value	0.6475	0.0484	0.3507	0.0061	0.6453
Perfect Comp. H=1	15.04***	16.44***	13.46**	17.25***	22.70***
P-value	0.0001	0.0001	0.0002	0.0000	0.0000
Wald Chi^2	241.23	52532.32	59.63	52974.18	57.12
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J-test (p-value)	0.9886	0.0771	0.727	0.4969	0.2272
Hausman Chi^2	0.71	47.27	8.08	34.09	19.99
P-value	0.9943	0.000	0.2327	0.0007	0.0672
Obs. (Groups)	186 (59)	99 (41)	207 (54)	210 (53)	187 (49)

Note: Time effects were included in models for Peru and Ecuador, but the results are not presented. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 5: Static Revenue Test (Long-run E-statistics of sampled MFIs in selected countries-FE2SLS) Nonconventional SE; FE models are preferred on the basis of Hausman tests between FE versus G2SLS or EC2SLS models.

	India	Indonesia	Philippines	Peru	Ecuador
log(car)	-0.006	0.144	0.035**	-0.091*	0.010
	(0.010)	(0.112)	(0.012)	(0.040)	(0.019)
log(fea)	0.019*	0.007	0.004	-0.029**	-0.007
	(0.009)	(0.008)	(0.008)	(0.010)	(0.006)
log(pea)	-0.015	-0.009	-0.009	0.019	-0.022
	(0.008)	(0.027)	(0.009)	(0.022)	(0.018)
log(aea)	-0.006	-0.015	-0.006	-0.0004	0.009
	(0.005)	(0.019)	(0.011)	(0.017)	(0.009)
log(glpta)	0.026	-0.037	0.037*	0.052	0.060
	(0.018)	(0.076)	(0.018)	(0.030)	(0.035)
lsize	0.060	-0.389	0.191*	-0.406**	-0.157
	(0.071)	(0.517)	(0.096)	(0.125)	(0.141)
Constant	-0.175	1.231	-0.458	1.020**	0.425
	(0.204)	(1.632)	(0.261)	(0.335)	(0.345)
Long-run E-statistic	-0.002	-0.017	-0.011	-0.011	-0.019
	(0.012)	(0.043)	(0.011)	(0.029)	(0.020)
LR Equilibrium, E=0	0.02	0.16	1.08	0.13	0.87
P-value	0.8925	0.6864	0.2994	0.7137	0.3515
Wald Chi^2	99.09	82.41	14.29	271.76	91.54
P-value	0.0000	0.0000	0.0265	0.0000	0.0000
Hansen J-test (p-value)	0.2278	0.7127	0.1768	0.5462	0.0729
Hausman Chi^2	53.40	45.18	7.76	21.99	19.04
P-value	0.0000	0.000	0.2566	0.0012	0.0041
Obs. (Groups)	275 (87)	112 (44)	229 (55)	240 (58)	217 (50)

Note: Time effects were not included. * p<0.05, ** p<0.01, *** p<0.001

Table 6: Dynamic Revenue Test (Panzar-Rosse H-statistics of sampled MFIs in selected countries)

	India	Indonesia	Philippines	Peru	Ecuador
L.log(intinc)	0.500**	-0.344	0.242*	0.040	0.213
	(0.161)	(0.291)	(0.103)	(0.647)	(0.413)
log(fea)	-0.129	-1.020*	-0.107	-0.255	-0.518
	(0.364)	(0.500)	(0.157)	(0.380)	(0.446)
L.log(fea)	0.081	0.143	0.142	0.060	-0.244
	(0.442)	(0.513)	(0.197)	(0.454)	(0.318)
log(pea)	-0.587**	0.046	-0.090	-0.583	-0.598
	(0.196)	(0.375)	(0.309)	(0.486)	(0.531)
L.log(pea)	0.430*	-0.650*	0.094	0.863	1.217
	(0.214)	(0.276)	(0.360)	(0.772)	(0.685)
log(aea)	-0.004	-0.186	-0.436	-0.306	-0.479
	(0.125)	(0.171)	(0.289)	(0.534)	(0.945)
L.log(aea)	0.026	-0.157	0.201	-0.119	0.367
	(0.154)	(0.150)	(0.288)	(0.924)	(0.714)
log(car)	1.386**	0.281	2.391***	3.539	1.629
	(0.499)	(2.543)	(0.544)	(3.008)	(1.457)
L.log(car)	-1.005**	0.572	-1.646**	-2.969	-1.947
	(0.326)	(2.032)	(0.504)	(2.152)	(1.617)
log(glpta)	1.372*	1.176	0.367	1.053	-0.183
	(0.590)	(1.029)	(0.351)	(1.072)	(1.078)
L.log(glpta)	-0.733	1.068	0.012	-0.670	0.930
	(0.472)	(0.927)	(0.480)	(1.486)	(1.021)
lsize	32.094***	30.947	59.433***	54.027	49.405*
	(3.837)	(26.674)	(9.669)	(33.745)	(18.942)
L.lsize	-23.286***	-7.762	-47.287***	-36.369	-35.752*
	(4.131)	(20.309)	(9.391)	(39.078)	(15.249)
Constant	-18.504**	-50.107	-23.930***	-37.691*	-30.189
	(5.683)	(45.461)	(3.851)	(16.147)	(15.368)

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Table 6: Dynamic Revenue Test (Panzar-Rosse H-statistics of sampled MFIs in selected countries) (contd.)

PR H-statistic	-0.721*	-1.159	-0.632	-1.144*	-1.596
	(0.292)	(0.888)	(0.503)	(0.494)	(1.204)
Monopoly H=0	6.11*	1.71	1.58	5.36*	1.76
P-value	0.0161	0.1993	0.2144	0.0245	0.1916
Perfect Comp. H=1	34.82***	5.92*	10.51**	18.84***	4.65*
P-value	0.000	0.0197	0.002	0.0001	0.0364
F-test	48.22	2227.45	41.90	101.95	57.12
P-value	0.000	0.000	0.000	0.000	0.000
Sargan	35.49	8.08	43.05	15.48	14.33
P-value	0.046	0.232	0.007	0.079	0.111
Hansen J-test (p-value)	0.701	0.811	0.508	0.519	0.151
AR (1)	0.025	0.232	0.008	0.570	0.275
AR (2)	0.197	0.911	0.189	0.942	0.093
Number of instruments	43	25	43	29	29
Lags used	2_2	2_2	2_2	2_2#	4_4§
Obs. (Groups)	203 (66)	85 (40)	208 (60)	221 (54)	148 (46)

Note: Time effects were included. #Instruments used in GMM style equation (difference) only. §Instruments used in GMM style equation (level) only. * p<0.05, ** p<0.01, *** p<0.001

Table 7: Dynamic Revenue Test: Long-run E-statistics of sampled MFIs in selected countries

	India	Indonesia	Philippines	Peru	Ecuador
L.log(1+roa)	0.421**	0.483***	0.725*	0.454	0.346**
	(0.155)	(0.112)	(0.304)	(0.553)	(0.127)
log(fea)	-0.002	0.028	-0.005	-0.011	0.017
	(0.013)	(0.015)	(0.010)	(0.020)	(0.009)
L.log(fea)	-0.001	-0.006	0.006	-0.003	-0.010
	(0.012)	(0.007)	(0.007)	(0.014)	(0.009)
log(pea)	-0.017*	-0.020	-0.028	-0.028	-0.033
	(0.006)	(0.019)	(0.019)	(0.034)	(0.031)
L.log(pea)	0.014*	0.016	0.029	0.034	0.017
	(0.007)	(0.016)	(0.019)	(0.028)	(0.022)
log(aea)	-0.001	-0.031***	-0.036*	-0.021	0.002
	(0.006)	(0.007)	(0.017)	(0.019)	(0.018)
L.log(aea)	0.001	0.015	0.030*	0.000	-0.002
	(0.005)	(0.011)	(0.014)	(0.010)	(0.018)
log(car)	0.016	0.008	0.122*	0.040	0.049
	(0.011)	(0.039)	(0.055)	(0.068)	(0.052)
L.log(car)	-0.013	-0.011	-0.119*	-0.044	0.008
	(0.010)	(0.036)	(0.053)	(0.040)	(0.034)
log(glpta)	0.023	-0.026	0.012	0.064	0.002
	(0.012)	(0.061)	(0.026)	(0.040)	(0.036)
L.log(glpta)	0.013	-0.010	-0.022	0.006	-0.001
	(0.016)	(0.030)	(0.027)	(0.037)	(0.042)
lsize	0.359	0.339	1.413**	0.884*	0.951
	(0.231)	(0.408)	(0.460)	(0.397)	(0.561)
L.lsize	-0.321	-0.366	-1.424**	-0.922*	-0.812
	(0.193)	(0.426)	(0.440)	(0.371)	(0.510)
Constant	-0.106	0.070	0.014	0.034	-0.323
	(0.187)	(0.113)	(0.187)	(0.106)	(0.172)

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Table 7: Dynamic Revenue Test: Long-run E-statistics of sampled MFIs in selected countries) (contd.)

LR E-statistic	-0.020	-0.023	-0.068	-0.060	-0.015
	(0.012)	(0.022)	(0.038)	(0.032)	(0.036)
LR Equilibrium E=0	2.96	1.11	3.31	3.61	0.17
P-value	0.0892	0.2988	0.0736	0.0624	0.6795
F-test	5.67	117.14	8.54	72.23	9.65
P-value	0.000	0.000	0.000	0.000	0.000
Sargan	34.98	53.77	48.83	13.46	26.72
P-value	0.052	0.000	0.001	0.265	0.268
Hansen J-test (p-value)	0.463	0.244	0.393	0.305	0.615
AR (1)	0.061	0.208	0.003	0.265	0.193
AR (2)	0.789	0.862	0.833	0.933	0.154
Number of instruments	43	41	43	31	43
Lags used[#]	2_2	2_3	2_2	2_2	4_4
Obs. (Groups)	254 (82)	97 (43)	242 (64)	262 (60)	192 (49)

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