Efficiency in Microfinance Cooperatives

Eficiencia en cooperativas de microfinanzas

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Abstract

In recognition of cooperatives' contribution to the socio-economic well-being of their participants, the United Nations has declared 2012 as the International Year of Cooperatives. Microfinance cooperatives make a large part of the microfinance industry. We study efficiency of microfinance cooperatives and provide estimates of the optimal size of such organizations. We employ the classical efficiency analysis consisting of estimating a system of equations and identify the optimal size of microfinance cooperatives in terms of their number of clients (outreach efficiency), as well as dollar value of lending and deposits (sustainability). We find that microfinance cooperatives have increasing returns to scale which means that the vast majority can lower cost if they become larger. We calculate that the optimal size is around $100 million in lending and half of that in deposits. We find less robust estimates in terms of reaching many clients with a range from 40,000 to 180,000 borrowers.

Keywords: microfinance institutions, efficiency, scale economies, social impact

Resumen

Las Naciones Unidas han declarado 2012 como el Año Internacional de las Cooperativas, en reconocimiento a su contribución al bienestar socioeconómico. Las cooperativas tienen una participación importante en el sector microfinanciero. Estudiamos su eficiencia y proporcionamos una estimación del tamaño óptimo de dichas entidades. Utilizamos el análisis de eficiencia clásico, que consiste en estimar un sistema de ecuaciones, e identificamos el tamaño óptimo de las cooperativas microfinancieras en términos de número de clientes (eficiencia en el alcance) así como en el valor en dólares de préstamos y depósitos (sostenibilidad). Encontramos que las cooperativas microfinancieras tienen rendimientos crecientes a escala, lo que significa que en su gran mayoría pueden reducir costes si crecen. Calculamos que su tamaño óptimo está alrededor de 100 millones de dólares en préstamos y la mitad en depósitos. Encontramos estimaciones menos robustas en términos de alcance a clientes, con un rango entre 40 000 y 180 000 prestatarios.

Palabras clave: instituciones de microfinanzas, eficiencia, economías de escala, impacto social

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Introduction

Microfinance Institutions (MFIs) provide financial services to marginal clients, typically avoided by traditional financial institutions. MFIs have diverse organizational structure and can operate as non-governmental organizations (or NGOs), non-bank financial institutions, microfinance banks, and as cooperatives. While there are few observed differences in the outreach and sustainability of various organizational forms, the performance of microfinance cooperatives is among the least studied (Mersland and Strøm 2008). The contribution of cooperatives including that of financial cooperatives (e. g., credit unions or MFI-cooperatives) to the socio-economic well-being of their participants remains important, however. In recognition of cooperatives' impact, the United Nations' General Assembly passed a resolution 64/136 on December 21st, 2009, declaring the year 2012 as the International Year of Cooperatives.

Understanding how efficient microfinance cooperatives are is important because cooperatives are some of the oldest organizations that remain relevant in microfinance. In fact, Mersland (2009) observes that "Historically, pro-poor banking has been dominated by [cooperatives] …, such as the 19th century savings banks, and the 19th century Schulze-Delitzsch and Raiffeisen cooperatives (Teck, 1968)". Cooperatives and savings banks still continue to flourish in several highly competitive markets (Christen et al 2004; Peachey and Roe 2006). Furthermore, in more mature bank-markets, there is little evidence that cooperative firms are less efficient than shareholder firms (Altunbas et al 2001; Crespi et al 2004). Recent Mix Market data show that, compared to non-cooperative MFIs, larger cooperatives offer considerably lower interest rate on their loan products and have the highest financial margins (adjusted for operating expenses). Mersland (2009) studies the cost of ownership of MFIs and finds that the cost variables related to market contracting favor co-operatives, whereas most cost-variables related to the practice of ownership favor shareholder type organizations and concludes that coexistence of ownership types is best for microfinance customers.

In practice, despite challenges associated with governance of financial cooperatives related to the one-share-one-vote principle, cooperatives persist and have proven resilient overtime. Little research, however, is devoted to the efficiency of microfinance cooperatives. The objective of this work is to find out how efficient MFIs-cooperatives are, and to provide estimates for the optimal size of such organizations. To this effect, we employ efficiency analysis consisting of estimating a system of a cost function and cost shares equations, typically employed in efficiency studies of banks and other financial institutions. Our analysis permits identification of the optimal size of cooperative MFIs in terms of both number of clients and size of the portfolio. We look at both dimensions because all MFIs including cooperatives have a double bottom line objective – serving as many poor clients as possible while remaining financially sustainable. Moreover, since all cooperatives provide savings and loans, efficiency analysis is different from the traditional analysis of microfinance institutions' efficiency in that we consider the impact on cost of both savings and deposits.

We find that microfinance cooperatives have increasing returns to scale which means that majority of them would benefit from expanding to a larger size. In particular, we calculate the optimal size at about $100 million in lending and half that amount in deposits. Less robust estimates of the optimal size in terms of outreach suggest that it is optimal to have between 40,000 to 180, 000 borrowers and at least a million depositors.

The rest of the paper is organized as follows. The second section discusses the relevant microfinance efficiency literature, section three describes the empirical method, data are summarized in section four, section five contains a discussion of the results, and section six offers conclusions.

2 Discussion of relevant literature

Studies that focus on efficiency of organizations are important because they can identify the optimal size of an organization which allows these institutions to reach the most clients at the lowest costs. While a multitude of papers have provided insights on the optimal size (scale economies) of commercial banks for various groups and banks and time periods (see Berger and Mester 1997, 2003; Berger 2007 for surveys of the literature), there are relatively few microfinance efficiency studies. The microfinance efficiency literature, similar to the banking efficiency literature, consists of two very different approaches – nonstructural and structural (Hughes and Mester 2008).

Traditionally, studies use a nonstructural approach whereby efficiency in MFIs is evaluated with industry benchmarks developed by the Microbanking Bulletin (MBB). In fact, these benchmarks have become so popular that efficiency in MFIs was, until recently, measured in terms of several popular ratios (see Balkenhol 2008, for a review and summary of the relevant ratios). Widespread use of the MBB performance ratios in conjunction with new data has been a marked improvement since most of the prior literature did not involve analysis of MFIs' financial results (Morduch 1999). Results from ratio analysis allow comparison of the institutions' performance change in time and to the averages for the industry. However, ratios have limitations as Gutiérrez-Nieto et al (2007) find that MFI performance rankings based on MBB ratios differ from rankings produced by nonparametric (DEA) efficiency analysis, widely used in banking.

Another group of nonstructural studies calculate profitability, efficiency, and productivity ratios and use them as dependent variables in regression analysis. This framework permits identification of factors that might contribute to MFI (under)performance and possibly identify ways for improvements (Cull et al 2007; Hudon and Traca 2011). While this nonstructural approach has merit, so far, it has not fully accounted for the multiple dimensions of organizational performance. For example, reaching more poor borrowers may increase the number of borrowers but it may also increase the costs and worsen financial sustainability ratios. That is, single equation regression analysis with efficiency ratios as explained variables does not permit simultaneous accounting for the dual objectives of the organization.

Applications of the alternative, structural approach to efficiency, more typical in the literature on efficiency in financial institutions and banks, are few and relatively recent. In 2007, Cull et al wrote: “The overall equation linking capital and labor inputs into profits and social change still proves difficult to master” (p. F107). The structural approach to which we are contributing is based on solid theoretical foundations and requires cost (or production) function estimation. The first such studies focused on analyzing efficiency of MFIs operating in a single country. Specifically, Paxton (2007) estimated scale economies in Mexico’s popular savings and credit institutions, while Leon (2009) studied cost efficiencies in Peru’s municipal banks in the 1990s, using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methods. Research with regional datasets includes Gutiérrez-Nieto et al (2007) who use DEA to evaluate the efficiency of MFIs in Latin America and Caudill et al (forthcoming) who study the efficiency and productivity of MFIs in Eastern Europe and Central Asia within the classical system of equations approach.

Most studies with cross-country datasets have used structural efficiency analysis to answer questions other than those that the classical approach can answer, namely, what is the optimal size and product mix (scale or scope economies) and elasticities of substitution among input factors. For example, Hartarska and Mersland (2012) focus on the impact of governance mechanisms that the literature suggests affect managerial (in)efficiency. For a sample of MFIs with rating reports from across the world, they estimate efficiency coefficients which subsequently are used as the dependent variable in the governance analysis. The efficiency part of the analysis is done via a stochastic cost frontier in which the cost function is similar to the cost function used in this study in that it accounts for the sustainability mission of MFIs because it assumes cost minimization. Specifically, to capture the outreach mission within the cost function, output is measured by the number of active clients following a cost function specification. Caudill et al (2009) use a two-stage mixture model based on the stochastic cost frontier approach to determine how MFIs’ efficiency changes over time.

Hermes et al (2011) find a tradeoff between sustainability and outreach using a one-stage SFA proposed by Battese and Coelli (1995) with data collected by the Mixmarket Information Exchange (www.mixmarket.org). They estimate a translog cost function consisting of standard variables, such as input prices and output quantities as well as controls for lending methodology and MFI type, and model the mean of the inefficiency term as a function of other control variables likely to impact inefficiency such as loan size and MFI age. The results suggest a tradeoff between efficiency and the poverty level of clients.

Another efficiency question important for cooperatives addressed by the literature is the existence and magnitudes of economies of scope from jointly providing savings and lending instead of only lending. These studies also estimate a cost function via a semiparametric generalization of Berger and Humphrey (1991). Hartarska et al (2011) show that there are substantial scope economies mainly due to fixed costs sharing by MFIs while there are scope diseconomies from operating costs sharing. These results suggest that borrowers and savers are likely different populations and that MFIs typically do not use knowledge from borrowers to design and improve savings products. Hartarska et al (2011) find that external factors related to the macroeconomic environment, level of financial development, population density and MFI specific technology affect significantly the magnitudes of estimated scope economies and need to be incorporated in such studies. Hartarska et al (2010) show that the mean values of estimated scope economies in MFIs do not differ if dollar values rather than savings and lending account numbers are used as the output (even in a dataset with many outliers such as the MIX market dataset) but that the distributions of the estimated economies are different. These papers estimate economies of scope at about 13 percent but also find that about a quarter of the MFIs would have operated under scope diseconomies if they were to provide both savings and loans thus suggesting that generalizations should be avoided.

This paper is closest to recent applications of the structural approach to efficiency which uses cross-country data to estimate scale economies in MFIs by the method of Seemingly Unrelated Regressions. Hartarska et al (forthcoming a) are the first to estimate scale economies of MFIs and to calculate elasticities of substitution between input factors for a large sample of rated MFIs. They found tradeoffs between sustainability and outreach in that optimal size is affected by the social outreach and sustainability objectives. Hartarska et al. (2012) estimate the cost minimizing size using an alternative dataset (maintained by MIX Market and also used in the present analysis) and focus on how the results are affected when social performance (breadth of outreach) is taken into consideration. This study finds overall increasing returns to scale but also several regional differences. They found that models not accounting for the social performance find constant returns to scale for MFIs in Eastern Europe and Central Asia, and increasing returns to scale for those in Latin America

(LA). Estimates accounting for the social outcomes show decreasing returns to scale in ECA and constant returns to scale in LA. Hartarska et al (forthcoming b) assess how scale economies are affected by the cost of capital subsidy, measured by the opportunity cost of equity. They find a difference between models with the cost of accumulated equity explicitly accounted which show that larger loan portfolios with fewer clients are optimal while typical models show smaller loan portfolio size but more active clients. The authors' interpretation is that these results fit the objective of subsidizing – to encourage MFIs to serve more and less wealthy borrowers.

None of these studies, however, has focused exclusively on cooperative MFIs. Clearly, previous work suggests that MFI heterogeneity, and thus organizational type matters and there may be important differences in the results for cooperative MFIs. Cooperative MFIs are intermediaries – all provide savings and loans while many other MFIs only lend. Moreover, cooperatives governance and structure are different because clients-owners are both borrowers and savers and the proportion of non-clients must affect management of a cooperative and their focus – sustainability or types of outreach. Therefore, this paper uses the same empirical methodology – structural approach and a system of equations but focuses on cooperative MFIs to estimate their economies of scale and optimal size.

3 Method

A structured approach to efficiency in organizations involves estimating either a profit or cost function to determine the optimal scale of the firm. For the microfinance industry, the cost function is preferable for two reasons. First, while some MFIs operate as for-profit organizations, the majority remain non-profit. Thus, while not all MFIs necessarily maximize profits, all strive to minimize cost. From a theoretical perspective, the use of a cost function is more appropriate for cases when firms are price takers in the input markets (labor and capital) and have some market power in the output (loan provision) market (Varian 1984). MFIs have some market power in serving the poor, but markets for inputs such as physical assets, financial capital, and salaries for (relatively) skilled labor are, by and large, competitive.

A cost function rather than a production function is used for another reason. Smith (1984) observes "Since it would be incongruous to model a credit union (CU) as maximizing profit or the return on equity (since members' share deposits in the CU cannot appreciate in value or be publicly traded), cost minimization is deemed to be the appropriate objective function". While in this paper Smith builds a theoretical model were the balance of net-savers and net-borrowers affects the objective of the cooperatives, in his later paper, Smith (1986) finds empirical evidence to support the standard cost function applications with cross-sectional data (Smith 1986).

The theoretical postulation of the cost function approach is that MFIs minimize costs subject to production technology constraint. The solution to this optimization problem generates the optimal costs expressed in terms of input prices and output quantities. The functional form for the cost function and the cost share equations (derived as $\partial lnC/\partial lnp_i$) are

$$ln(C) = \alpha_0 + \sum_j \alpha_j ln\,(p_j) + \sum_k \beta_k\, ln(y_k) + \frac{1}{2}\sum_j\sum_i \gamma_{ij} ln\,(p_i)\, ln(p_j) + \frac{1}{2}\sum_k \delta_k ln\,(y_k)^2 + \sum_k \sum_j \rho_{kj}\, ln(y_k)\, ln(p_j) + \sum_m \theta_m ln\,(z_m) + \varphi_t T + ln\,(v) \quad (1)$$

$$S_i = \frac{dln(C)}{dln(p_i)} = \alpha_i + \sum_j \gamma_{ij} ln\,(p_j) + \sum_k \rho_{ki} l\,n(y_k) + ln\,(\varepsilon) \quad (2)$$

where C is total cost, y_k is the output quantity, with k=1 for number of active borrowers or dollar value of loan portfolio and k=2 for number of savers or dollar value of deposits, p_j's are input prices, with j=1 and 2 for operating expense and financial capital, z_m are control variables: portfolio at risk of 30 days or more and percent of women borrowers, T is time trend, S_i is the i's input share of the total cost. The parameters to be estimated are α_0, α_j, β_k, γ_{ij}, δ_k, ρ_j, θ_m, and ϕ_t. All the variables are mean scaled. Standard restrictions of homogeneity and symmetry with respect to input prices and output can be imposed directly as:

$$\gamma_{ij} = \gamma_{ji}, \sum_j \alpha_j = 1, \sum_i \gamma_{ij} = 0, \sum_j \gamma_{ij} = 0, \sum_j \rho_{kj} = 0 \quad (3)$$

Homogeneity condition can be imposed by dividing costs and inputs by one input price and this is the approach we have taken. The system described by equations (1) and (2) is estimated using the standard seemingly unrelated regressions (SUR) technique.

When MFIs operate at minimum costs, we say there are constant returns to scale. This is the case when the sum of estimated coefficients on the outputs ($\sum_k \rho_{ki}$) is one and firm size is optimal. When this sum is bigger than one, there are decreasing returns to scale or diseconomies of scale and, when it is smaller than one, there are increasing returns to scale, or economies of scale. With increasing economies of scale, an increase in output causes a less than proportional increase in total cost, holding all input prices constant. With increasing returns to scale, MFIs can lower costs by increasing their size by expanding output to take advantage of cost-saving opportunities. With scale diseconomies, when the sum of the coefficients on output is bigger than one, (many) MFIs are too big and can decrease costs by scaling back output. Thus, we look at the sum of estimated coefficients for the impact of the output variables on costs ($\sum_k dTC/dy_{ki}$ or $\sum_k \rho_{ki}$) to see if MFIs can grow further to minimize per unit costs.

This setup allows capturing the social impact objective of the MFIs because we can measure outputs with its social dimension – the number of active borrowers served and savers (as in Caudill et al 2009; Hartarska et al 2011). MFIs are diverse and operate in diverse environment making it impossible to prescribe what loan products they should offer since what is optimal in one country may be inadequate in another. In some places, MFIs reach less poor clients than in others, but we do not explicitly focus on this here. We subscribe to the argument that MFIs can manipulate loan products and size to serve as many clients as possible in their environment and in a sustainable manner. Therefore, we capture social performance by the breadth of outreach, namely the ability of MFIs to serve many poor clients. To underline the importance of accounting for social impact we compare our results to results from traditional banking specifications where outputs are measured by the dollar value of loans and deposits, a measure often used by both academics and MFI practitioners.

We measure the cost of capital in two ways. For the main part of the paper, we follow the more typical methods and use the price of borrowed capital calculated as the interest paid over liabilities (more precise calculations are not possible with our data) and total costs are operating and financial expenses as is typical in this specification. In addition, we calculate the weighted price of capital by measuring the cost of equity by the country deposit rate (adjusted by the relevant currency exchange rate) collected from the International Financial Statistics at IMF, and include the additional cost of equity and the value of equity (in addition to borrowed capital) in the total cost computation. The differences in the estimated results can therefore be attributed to the role of the subsidy since equity's opportunity costs can now affect total costs (Hartarska et al forthcoming b).

Since we recognize that environmental factors as well as MFI specific factors affect MFI costs, we add several control variables. For example, cost function estimation of financial institutions must also account for the credit risk typically measured by non-performing loan ratios. This is needed because lower asset quality (or higher nonperforming loan ratio) requires more resources to manage the higher risk and, if asset quality is not accounted for, estimated scale economies will be reduced. Thus, results may show that there are economies of scale while, in fact, when risk is incorporated financial institutions have constant returns to scale, i. e., operate at the minimum costs (Hughes and Mester 1998). Thus, we also control for the level of risk using a variable measuring the ratio of loans overdue more than 30 days to total portfolio, which is a standard ratio used by MFIs to measure the risk level of their loan portfolio. Similar arguments hold in MFI cooperatives which are oriented towards serving women because women are more socially marginalized and thus managing risk associated with different risk type clients could affect costs. Therefore, to control for this impact, we add the percentage of women borrowers to capture MFIs orientation toward serving more socially marginalized women.

Since technology changes over time, banking efficiency studies add a time trend as a proxy for technical progress. Technical progress is expected to reduce total cost since costs should decrease with time and is captured by the derivative of cost with respect to time, namely the coefficient on the time trend. We also control for the country specificity by including country dummies (not shown, available on request). Finally, we estimate two specifications, one with outputs measured by the social impact and one by the dollar value of the portfolio to calculate the optimal MFI size predicted by each of the specifications following Hartarska et al (forthcoming b).

4 Data

The data for the analysis is from the largest dataset available for MFIs worldwide, maintained by the Mix Market Information Exchange database. We use data for all MFIs organized as cooperatives with sufficient financial statement data to use in cost function estimation. The total number of useful annual observations is about 550 which represent 216 cooperative MFIs from 41 countries for the period 2003-2010. The dataset is an unbalanced panel with 2.5 observations per MFI on average.[1]

Summary statistics and variable symbols are presented in Tables 1a and 1b for the two subsamples used in the analysis. It shows that total cost (TC) calculated as the sum of input prices times their quantity) was 2.2(1.9) million US dollars on average for the larger and smaller samples respectively, varying from \$20,000 to \$97.5 million for an MFI in 2010 USD equivalents. The price of capital is 8.6 (8.7) percent with a range from 1 to 43 percent. This price was 8.3 percent if we account for the value of the equity and goes from less than 1 to 32 percent. The average annual operating expenses per employee (P_l) are \$9,138 (\$9,221, respectively). For the MFIs in the sample, the average loan portfolio is \$20 million (\$18.4 million respectively) and it varies widely from \$70,000 to \$792 million. The average number of borrowers is 15,000 (13,000 respectively) and varies from only 60 in the smallest MFI to 0.5 million for the largest MFI.

Additional variables that affect total costs included in the model estimated with the smaller sample are the share of women borrowers with the average of 52 percent ranging from less than 1 to 100 % and the risk measure-portfolio at risk (loans overdue for more than 30 days) which is less than 7 percent on average and varying from zero to 86.5 percent in the worst case. To explore possible learning-by-doing effect, we control for firm age by including three categories: new (the base) consisting of 9 % MFIs up to 5 years old, young for MFIs 5-8 year old representing 22 % of the observations, and mature for MFIs older than 8 years which represent 69 % of MFIs in the sample.

1 Our final dataset consists of relatively larger MFIs coops reporting to MIX Market. For example, in our sample the average size of the portfolio is \$18 million while it is \$12 million for all MIX Markets coops, the number of borrowers on average is about 13,000 but 9,300 in the population. The average volume of savings is the same at \$15 million in both samples but it is distributed among 40,000 savers in our sample and to about 30,000 savers in the all MIX Market reporting coops. We assume that our sample consists of larger coops because these are likely to be more transparent in their financial transactions and to provide more detailed balance sheet data necessary for cost function estimation.

Variables	Symbol	Obs	Mean	Std. dev.	Min	Max
Input & output						
Total cost (US$ millions)	TC	550	2.2	6.3	0.02	97.5
Labor cost	Pw	550	9,138	5,700	379.4	29,675
Financial cost (%)	Pf	550	8.6	7.6	0.03	42.9
Loan portfolio (US$ millions)	Y1	550	20.2	56.1	0.07	792
Deposits (US$ millions)	Y2	550	17.7	59.2	0	958
Number of active borrowers (thousands)	Y1	540	14.8	39.4	0.06	554
Number of depositors (thousands)	Y2	540	43.4	125.7	0	2,035

Table 1a
Summary statistics, larger sample.

Variables	Symbol	Obs	Mean	Std. dev.	Min	Max
Input & output						
Total cost (US$ millions)	TC	470	1.9	4.7	0.02	67.6
Labor cost	Pw	470	9,221	5,761	379.4	29,674.6
WACC (%)	P_{WACC}	452	8.7	6.6	0.01	31.9
Financial cost (%)	Pf	470	8.9	8.0	0.03	42.9
Loan portfolio (US$ millions)	Y1	470	18.4	45.7	0.10	618
Deposits (US$ millions)	Y2	470	15.1	43.8	0	729
Number of active borrowers (thousands)	Y1	470	12.8	32.1	0.10	550.6
Number of depositors (thousands)	Y2	465	38.6	94.7	0	1,213.9
Control variables						
Loan past due > 30 days (%)	Risk	470	6.7	7.5	0.01	86.5
Women borrowers (%)	Women	470	52.0	20.3	0.75	100
Young (%)	Young	470	22.3	41.7	0	100
Mature (%)	Mature	470	68.5	46.5	0	100

Table 1b
Summary statistics, smaller sample.

5 Results

The results from the cost function estimation are presented in Table 2. The results are for two samples, a smaller sample for which we can estimate full specification with all necessary controls and a larger sample that does not have data on the control variables but includes all standard cost function variables: input prices, outputs quantities, time trend, and country dummies.[2] The first column contains the results from the larger sample using the same specification, while estimates of the smaller sample are in the second column (for comparison purposes). The third column contains results from a specification that includes controls for age of the MFI, the level of risk, and orientation toward female clients. Such representation allows viewing the results not only from the most complete specification (Model 3) but given data limitations to compare these results with results from the larger dataset (Model 1). Corresponding models with output measured by the number of active borrowers and active savers instead of the volume of loans and savings to capture the outreach impact is presented in Table 3.

All regressions in Tables 2 & 3 satisfy the required properties of the cost function. As typical in a cost function with a system of equations, the model has a good statistical fit as indicated by the high cost function R-squared. Unsurprisingly, almost all of the variables and their interactions are statistically significant.

Overall, the results suggest that microfinance cooperatives exhibit increasing returns to scale because the sum of the output coefficients is smaller than one thus the average costs would fall if MFIs were bigger. The sum of the values of the output coefficients determines the returns to scale of MFIs cooperatives. When the sum is larger than one we have decreasing returns to scale (coops are too large), when it is exactly one then there are constant returns to scale and coops have optimal size. When the sum is smaller than one, as we find in all of our specifications, then there are increasing returns to scale and MFIs could have lower per unit output costs if they grew bigger.

The results further suggest that lending and saving have almost the same marginal impact on costs with one additional dollar in savings a bit more expensive to collect than one additional dollar is to lend. This qualitative difference is preserved in all three specifications in Table 2. We observe that there is no big difference in the estimated coefficients from the two samples. In terms of the control variables contained in column 3, we note that coops with one percent higher loans overdue 30 days or longer have 2.9 % lower costs, which is surprising since we expect risker loans to be associated with higher, not lower, costs. A possible explanation of this result is that MFIs target riskier borrowers who may become delinquent but do not default or that credit unions charge fees to compensate for borrowers delinquency. We find that more dollars lent to women-clients, considered risker borrowers because of their limited repayment capacity, is costlier with and one additional percent of dollars in loans to women associated with 8 % higher costs.

While there is no difference in the cost structure between new cooperatives (less than 3 years old) and those 5-8 years or younger, the group older than 8 years has on average 10 percent lower costs than new cooperatives. These results suggest that there is learning by doing taking place

2 The dataset likely includes fewer smaller coops than the population of coop MFIs because the most complete data needed for a structural efficiency analysis are provided by larger networks. Smaller cooperatives may not have the resources or incentives for improving financial disclosure. While the data likely comprises the larger coops in the industry, possible bias may not be large because smaller coops are unlikely to have lower average costs.

Variables	(1)	(2)	(3)
Y_1($)	0.415***	0.408***	0.405***
	(0.046)	(0.050)	(0.049)
Y_2($)	0.469***	0.492***	0.505***
	(0.043)	(0.048)	(0.047)
P_f	0.582***	0.584***	0.587***
	(0.008)	(0.009)	(0.009)
P_f^2	0.154***	0.157***	0.158***
	(0.005)	(0.005)	(0.005)
Y_1^2	0.184***	0.180***	0.186***
	(0.039)	(0.042)	(0.041)
Y_2^2	0.204***	0.221***	0.227***
	(0.031)	(0.034)	(0.034)
Y_1*Y_2	–0.178***	–0.181***	–0.186***
	(0.032)	(0.035)	(0.034)
Y_1*P_f	0.049***	0.049***	0.047***
	(0.008)	(0.009)	(0.009)
Y_2*P_f	0.010	0.008	0.010
	(0.008)	(0.008)	(0.008)
Risk			–0.029**
			(0.012)
Women			0.082***
			(0.028)
Young			-0.014
			(0.044)
Mature			–0.100**
			(0.043)
Time trend	0.008	0.008	0.012
	(0.007)	(0.008)	(0.008)
Constant	0.914***	0.897***	0.990***
	(0.122)	(0.122)	(0.126)
Observations	550	470	470
R^2	0.946	0.948	0.950
Ret. to scale	.88	.90	.91
Optimal scale (US$ millions)			
Borrowers	$106	$101	$97
Depositors	$70	$51	$48

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2

Cost function, output measured by the dollar value of loans and savings.

Variables	(1)	(2)	(3)
Y_1 (#)	0.475***	0.547***	0.549***
	(0.052)	(0.058)	(0.058)
Y_2 (#)	0.383***	0.308***	0.304***
	(0.047)	(0.052)	(0.052)
P_f	0.500***	0.494***	0.495***
	(0.010)	(0.011)	(0.011)
P_f^2	0.128***	0.127***	0.129***
	(0.005)	(0.006)	(0.006)
Y_1^2	0.105*	0.182***	0.188***
	(0.057)	(0.064)	(0.064)
Y_2^2	0.082***	0.085***	0.085***
	(0.028)	(0.030)	(0.030)
Y_1*Y_2	-0.065*	–0.096**	–0.103**
	(0.038)	(0.042)	(0.041)
Y_{2*} P_f	0.009	0.004	0.005
	(0.008)	(0.009)	(0.009)
Y_2* P_f	–0.009	–0.009	–0.009
	(0.006)	(0.007)	(0.007)
Risk			–0.003
			(0.022)
Women			–0.176***
			(0.053)
Young			–0.070
			(0.082)
Mature			–0.111
			(0.081)
Time trend	0.026**	0.018	0.018
	(0.013)	(0.015)	(0.015)
Constant	0.135	0.140	0.072
	(0.219)	(0.220)	(0.229)
Observations	532	465	465
R^2	0.848	0.830	0.833
Ret. to scale	.85	.85	.85
Optimal scale (thousands)			
Borrowers	181	45	43
Depositors	1,873	1,214[a]	1,214[a]

[a] This is the maximum value, since calculated optimal scale is out of data range.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3
Cost function, output measured by the number of active borrowers and savers.

which is what is to be expected but that this learning takes at least 8 years and not the usual 3 to 5 years expected from microfinance banks such as those associated with ProCredit group. There is no statistically significant difference between cooperatives in the 3-8 and over 8 years groups.

Calculated returns to scale and the corresponding optimal size for a cooperative MFI, in terms of loan portfolio and deposits size for each specification are presented at the bottom of each column. We note that the results from the smaller sample suggest that the optimal size of a gross loan portfolio is about 100 million dollars and savings portfolio about half that size. The results for the larger sample suggest a somewhat larger size for both loans and deposits. The optimal loan size is about 5 times the mean value of loans (20 million) and deposits (16 million) and suggests significant room for growth since the median values are $4 million for loan portfolio and $3 million for deposits. Thus, results suggest that the vast majority of cooperative MFIs could realize significant gains if they were able to grow, *ceteris paribus.*

It is important to note, however, that potential increase in size in cooperative MFIs may come from either expanding their membership or by increasing in business with non-members, which is likely to affect the governance structure as well as the objectives that the MFI members value. That is why the ceteris paribus (all else equal) assumption is strong in this context and the optimal size results should be interpreted with this in mind.

Results from an identical specification except that outputs are measured by the number of active borrowers to capture the outreach mission of the cooperative MFIs are presented in Table 3. These results are very similar to results in Table 2 because we also find increasing returns to scale indicating that larger cooperative MFIs are more cost efficient. One interesting difference is that the marginal impact of the two outputs is now reversed. Specifically, it is more expensive to reach one more borrower than it is to get one additional depositor and the wedge here is larger than that in Table 2. This suggests that, for cooperative MFIs, attracting depositors from the target clientele is easier than reaching more borrowers. It is important to note, however, that our method and results do not account for possible the poverty level of both types of clients – active borrower or active savers. The results are consistent with Hartarska et al (2011) who study efficiency gains from offering services to both borrowers and depositors (scope economies) and argue that borrowers and savers in MFIs are likely to be at different level of poverty.

In these specifications, we do not find that risk and age affect costs of cooperatives. However, reaching borrowers is less costly in that one additional percent of women borrowers is associated with 17 % lower costs. This is the opposite of the results when outputs are measured by the volume of loans and savings and suggests that loans size is important since more women are likely to get smaller loans and smaller loans are costlier to administer.

The calculated optimal size in terms of number of clients is presented at the bottom of the column of Table 3. While the calculated increasing return to scale are the same across specifications (0.85), there are differences in the predicted optimal scale with those from the larger sample results indicating almost four times larger optimal number of borrowers than the 43,000 found with the smaller sample. Comparisons with the mean values of the small samples suggest that this number (43,000 borrowers) is several times the mean of 13,000 and over 10 times the median sample value of 3,000.[3] The last two models do not produce converging optimal number of active savers suggesting that the optimal number may be about a million savers (the maximum in the sample) and thus need to be considered with caution.

Table 4 presents the results from an extension which uses different values for the cost of capital – weighted average cost of capital. In previous specifications, the price of financial capital was calculated as the interest paid over liabilities (more precise calculations are not possible with our data). In this extension, we calculate the weighted price of capital by measuring the cost of equity by the country deposit rate to account for the equity's opportunity costs.

In general, the results from Table 4 are consistent with these in Tables 2 & 3 but there are small differences in the optimal size from specifications accounting for, and those not accounting for, the equity subsidy as well as from the measures of output. First, when the cost of equity subsidies is accounted for, it is more costly to lend and reach many borrowers compared to collecting deposits because the coefficient on Y (measured by the dollar value of the portfolio and the number of active borrowers) is larger than that on savings (in dollars and number of active savers). This makes the cost of subsidy result close to the results in Table 3 where output is measured by the number of active clients. The predicted optimal scale is close to but less than 100 million in portfolio but it is over 100 million in savings. The optimal predicted scale incorporating the cost of equity show an optimal size close to 40,000 borrowers and close to a million (780,000) savers, similar to the results in Table 3 especially in terms of the number of borrowers.

These results suggest that, for cooperative MFIs, the cost of equity does not lead to as large a difference as in other types of MFIs (other than cooperatives), likely because equity in cooperatives is typically not donated. For the majority of non-cooperative MFIs, Hartarska et al (forthcoming a) found that, when the cost of equity subsidy is taken into consideration, the recommendation would be to encourage MFIs to grow to a much large portfolio size in order to minimize costs and maintain sustainability compared to when the cost of subsidy is not explicitly valued.

The optimal size estimated by the model accounting for the equity subsidy and output in terms of the number of clients predicts fewer active borrowers (36,000) compared to the model without the equity sub-

3 The value predicted by the larger sample is even larger at 181,000 borrowers which in itself is at least four times higher than the prediction of the smaller sample.

Variables	(1)	(2)
	Lending and deposits	Lending and deposits
Y_1($)	0.596***	
	(0.041)	
Y_2($)	0.317***	
	(0.039)	
Y_1(#)		0.560***
		(0.057)
Y_2(#)		0.329***
	(0.039)	(0.052)
P_{WACC}	0.634***	0.542***
	(0.008)	(0.010)
$P_{WACC}{}^2$	0.143***	0.097***
	(0.005)	(0.006)
Y_1^2	0.150***	0.218***
	(0.033)	(0.067)
Y_2^2	0.174***	0.112***
	(0.026)	(0.031)
Y_1*Y_2	–0.145***	–0.130***
	(0.027)	(0.043)
Y_{1^*} P_{WACC}	0.056***	0.016*
	(0.009)	(0.009)
Y_{2^*} P_{WACC}	-0.008	–0.020***
	(0.008)	(0.006)
Risk	–0.016*	–0.007
	(0.009)	(0.022)
Women	0.016	–0.198***
	(0.022)	(0.054)
Young	0.024	–0.094
	(0.036)	(0.086)
Mature	–0.002	–0.107
	(0.034)	(0.083)
Time trend	0.003	0.027*
	(0.006)	(0.015)
Constant	–0.053	–1.102**
	(0.198)	(0.445)
Observations	452	448
R^2	0.851	0.858
Returns to scale	.91	.89
Optimal scale		
Borrowers	$78 Millions	36,000.00
Depositors	$119 Millions	781,000.00

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Table 4
Cost function, outputs in dollars and number of active clients, with weighted average cost of capital (WACC).

sidy – over 42,000 (or 180,000 according to the larger sample) of active borrowers. There seems to be a difference between models accounting for the cost of accumulated equity suggesting similar volume of loans and clients and models ignoring the cost of equity suggesting smaller loan portfolio for the same number of clients. This interpretation is consistent with the objective of subsidizing – encouraging MFIs to serve more, less wealthy borrowers.

Finally, computed elasticities of substitution between inputs and own price elasticities are contained in Table 5. The own price elasticities (including Allen own price elasticity) are negative as required and inelastic. Since we use two input prices – one measured by the operating expense per employee ("labor") and the other by the cost of capital, elasticities are harder to interpret. We find that labor and financial capital are inelastic substitutes. This means that very large change in the price of labor (measured by operating cost per employee) will be needed to substitute it with capital. Alternatively, very large changes in price of capital will be needed to induce more use of labor. The shortcoming of the data is that we do not have separate data on the prices of labor and the physical and financial capital. Nevertheless, the results reveal that cooperatives will not be able to costlessly adjust to shocks to either of their major inputs.

Variable	Y($)	Y(#)
Allen LF	0.37	0.48
Allen LL	-0.34	-0.45
Allen FF	-0.4	-0.52
OWN LL	-0.18	-0.23
OWN FF	-0.19	-0.25
Shares		
Labor	0.52	0.52
Finance	0.48	0.48

Table 5
Elasticities.

	Dollar values * US$ millions			***# of active clients*** thousands		
	Optimal	Mean	Median	Optimal	Mean	Median
Lending (smaller sample)	97	20 (50)	4	43	13 (32)	3
Savings (smaller sample)	48	16 (49)	3	1,200[a]	38 (95)	9
Lending (larger sample)	106	22 (62)	4	181	15 (40)	3.5
Savings (larger sample)	70	19 (67)	3	1,800	44 (13)	10

[a] This is maximum value of the sample, since estimates are outside our data range.
Table 6
Optimal lending and deposits in dollars and in number of active clients, comparison with the mean and median values

6 Conclusions

The importance of cooperative organizational structures such as financial cooperatives and microfinance cooperatives has been emphasized with the United Nations announcing 2012 as the International Year of Cooperatives. Yet, little is known about what makes cooperatives successful in microfinance. In this paper, we use efficiency analysis to estimate returns to scale and to compute the optimal size of microfinance cooperatives based on recent panel data from Mix Market.

We employ a classical structural approach which estimates a system of equations consisting of a cost function and cost shares. We find that cooperatives operate with increasing returns to scale and that the cost minimizing scale for a cooperative is about 100 million in lending and about half of that in savings. It is less clear, however, what the optimal number of borrowers and savers is but it varies from a lower bound of about 40,000 borrowers to several times that. In terms of the number of savers, we do not find robust results on what number of savers would be associated with constant returns to scale (cost minimizing cooperative) but it is likely a very large number close to a million, which is outside of the boundaries of our sample.

We conclude that, since the industry exhibits increasing returns to scale, the vast majority of microfinance cooperatives are likely to substantially lower their costs with expansion or possibly through consolidation. It is important to note that cooperatives grow through networks organized in multiple levels. For example, in West Africa, microfinance cooperatives are generally organized in networks of three levels (local – regional – central). Thus, the internal architecture of a cooperative network would vary and a network of 180,000 borrowers with only three local coops (with 60,000 borrowers each) will differ substantially from a network with the same number of borrowers but comprising 120 local coops (with 1,500 borrowers each).[4] Thus, expansion strategies in these two examples will be very different.

Future work should be directed toward understanding efficiency of microfinance cooperatives in the context of a more detailed and larger dataset. Our results suggest that there is a significant heterogeneity in cooperative MFIs and that future work may need to focus on a less aggregate level of analysis, e.g., on efficiency analysis in cooperative MFIs and their networks within a country. For this purpose, detailed data collection from smaller cooperative MFIs should be encouraged via their networks and other professional organizations.

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Appendix

Country	2003	2004	2005	2006	2007	2008	2009	2010	TOTAL
Afghanistan	0	0	0	1	1	1	1	0	4
Albania	0	0	0	1	1	1	1	0	4
Bangladesh	0	0	0	0	0	0	1	0	1
Benin	0	1	0	1	3	2	0	0	7
Bolivia	0	0	1	1	2	2	2	2	10
Brazil	0	0	0	1	1	2	2	1	7
Bulgaria	0	0	0	2	3	3	1	0	9
Burkina Faso	0	1	0	1	1	2	2	0	7
Burundi	0	0	0	0	0	1	1	0	2
Cameroon	0	0	1	0	2	3	3	0	9
Central African Republic	0	0	0	0	1	1	1	0	3
Chad	0	0	0	0	1	1	1	0	3
Chile	0	0	1	1	0	0	0	0	2
Colombia	0	0	0	0	0	1	6	3	10
Congo	0	0	0	0	0	0	1	0	1
Croatia	0	0	1	1	0	0	0	0	2
Ecuador	5	6	7	19	21	25	24	13	120
El Salvador	0	0	0	0	0	1	1	1	3
Guinea	0	0	0	1	1	1	1	0	4
India	0	0	3	3	3	3	2	0	14
Indonesia	0	0	0	2	3	3	2	2	12
Kyrgyzstan	0	0	0	0	0	1	1	0	2
Macedonia	0	0	2	2	2	2	2	1	11
Madagascar	0	0	1	3	3	5	5	0	17
Malawi	0	0	0	0	0	1	0	0	1
Mali	1	2	2	3	4	4	4	0	20
Mexico	0	1	1	0	0	1	1	1	5
Nepal	0	0	0	0	2	6	2	1	11
Nicaragua	0	0	0	1	2	2	2	0	7
Niger	0	0	0	1	2	1	1	0	5
Panama	0	0	0	1	1	1	1	0	4
Paraguay	0	0	1	1	1	0	0	0	3
Peru	0	2	2	3	5	10	9	10	41
Philippines	5	2	1	1	0	0	1	0	10
Russia	1	5	7	13	21	56	19	0	122
Rwanda	0	0	0	1	1	2	2	0	6
Senegal	2	3	0	6	6	4	7	0	28
Sri Lanka	0	0	0	0	1	1	1	0	3
Togo	0	0	1	3	4	3	2	0	13
Uganda	0	0	0	0	0	1	0	0	1
Uzbekistan	0	0	0	0	0	2	4	0	6
Total	14	23	32	74	99	156	117	35	550

Table 1
Distribution of cooperative MFIs by region and year.

Variable	Symbol	Africa	EAP	EAC	LAC	South Asia
Inputs & outputs						
Total cost (US$ millions)	TC	2.0	0.5	0.8	4.2	0.6
		(2.78)	(0.60)	(1.04)	(10.70)	(0.80)
Labor cost	P_l	5773.4	2634.4	11613.3	12731.2	2165.9
		(3977.06)	(1937.10)	(6076.76)	(4736.49)	(1528.22)
Financial cost	P_f	2.5	6.5	17.8	6.0	7.6
		(2.11)	(4.53)	(8.06)	(2.13)	(2.42)
WACC	P_{wacc}	4.5	6.6	15.4	5.9	7.0
		(3.39)	(4.07)	(7.19)	(2.15)	(2.85)
Loan portfolio (US$ millions)	Y1($)	21.7	2.3	4.7	38.9	3.8
		(32.20)	(1.99)	(8.89)	(93.40)	(4.24)
Deposits (US$ millions)	Y2($)	24.3	1.4	2.6	32.6	1.7
		(42.40)	(1.29)	(3.29)	(99.90)	(1.79)
Number of active borrowers (thousands)	Y1(#)	25.3	12.8	1.9	17.4	20.4
		(30.92)	(20.88)	(3.05)	(56.11)	(28.85)
Number of depositors (thousands)	Y2(#)	96.6	20.9	1.5	47.3	30.7
		(130.20)	(30.54)	(2.48)	(165.90)	(35.75)
Control variables						
Loan past due > 30 days	Risk	9.1	6.6	5.9	6.2	4.7
		(8.27)	(7.34)	(8.93)	(5.34)	(8.68)
Women borrowers (%)	Women	47.2	69.3	53.8	48.6	69.4
		(25.65)	(21.80)	(17.65)	(14.29)	(31.58)
Young	Young	10.2	31.8	34.2	18.7	21.2
		(30.43)	(47.67)	(47.59)	(39.10)	(41.51)
Mature	Mature	84.3	50.0	48.4	76.8	75.8
		(36.57)	(51.18)	(50.14)	(42.29)	(43.52)
Total assets (US$ millions)	Assets	34.7	2.9	5.2	46.5	5.3
		(57.40)	(2.38)	(9.61)	(112.00)	(6.86)
Observations		**127**	**22**	**156**	**212**	**33**

Table 2
Summary statistics by region.