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Which Microfinance Institutions Are Becoming More Cost Effective with Time? Evidence from a Mixture Model

Microfinance institutions (MFIs) play a key role in many developing countries. Utilizing data from Eastern Europe and Central Asia, MFIs are found to generally operate with lower costs the longer they are in operation. Given the differences in operating environments, subsidies, and organizational form, this finding of increasing cost effectiveness may not aptly characterize all MFIs. Estimation of a mixture model reveals that roughly half of the MFIs are able to operate with reduced costs over time, while half do not. Among other things, we find that larger MFIs offering deposits and those receiving lower subsidies operate more cost effectively over time.

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MICROFINANCE INSTITUTIONS, OR MFIs, serve as important providers of credit to poorer borrowers and thus can play a significant role in programs to alleviate poverty and promote economic opportunity in nations around the world (Morduch 1999a, Zohir and Matin 2004). These institutions make loans to borrowers

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who seek relatively small amounts and who may be viewed as too risky by larger conventional lenders. Quite often, MFIs operate with subsidies from charitable or governmental agencies. There appears to be considerable heterogeneity in the microfinance industry in terms of institution size, sustainability, and clientele served. Worldwide, the leading 10% of MFIs (about 150 institutions) serve approximately 75% of all microfinance clients, with the remainder served by thousands of small and heterogeneous institutions with varying degrees of sustainability (www.themix.org). Given their important role in providing credit to underserved individuals and the use of subsidies from various sources to support them, MFI operations should be well understood. One important question is whether MFIs are becoming more cost effective over time, particularly if any improvements can reduce or eliminate the need for subsidies. We are particularly interested in whether all MFIs appear to improve at the same rate, and whether there are identifiable factors associated with any detected differences.

There are several novel features of our study to answer these key questions. First, we have access to a unique database on MFIs operating in the Eastern Europe and Central Asia (ECA) region for 2003 and 2004. Second, we are among the first to estimate a statistical cost function using data on MFIs, although the practice is commonly applied to banking institutions. Finally, we are among the first to provide an analysis of the operations of nongovernmental organizations (NGOs) in the ECA region.

In general, it would be expected that firm operating performance should improve with time, *ceteris paribus*. In the case of MFIs, this is both an understatement and an oversimplification. For MFIs, time is vitally important to offset the information asymmetries present. Both the lenders and the clientele learn over time.

To illustrate the importance of time in the microfinance production process and to highlight some of the time-related effects, we consider what might be the case of a typical microfinance lender. An MFI may begin lending operations as an NGO or some other form of nonprofit entity. They are in the business of making small loans to customers who are not generally serviceable by the commercial banking sector. The MFI clientele typically lacks either credit histories, or collateral, or both. Given time, successful borrowers, whether individuals or members of a borrowing group, will exhibit responsible behavior and generate credit histories, thus providing some of the information absent when the MFI began operations. If these borrowers are very successful they may also generate collateral.

While the situation is changing on the clientele side with the passage of time, improvements in the productivity of the MFI itself are also likely to occur. Navajas, Conning, and Gonzalez-Vega (2003) and Gonzalez-Vega et al. (1996), when discussing Bolivia, describe the evolution of an MFI from an NGO to a for-profit bank. In their studies, they detail several advantages in the form of various types of capital passed from the NGO to the bank. While they deal with individual cases, generalizing some or all of the detailed advantages to maturing MFIs is not far fetched, particularly as one considers how the passage of time should affect an MFI.

Several possible benefits of the passage of time on microfinance performance are pointed out by Gonzalez-Vega et al. (1996): (i) the lending technology is proven and improved through several years of experimentation, development, and adjustment; (ii) the MFI accumulates a stock of information capital about the clientele and the environment; (iii) the MFI develops client relationships and identifies well-performing clients; (iv) the MFI accumulates the human capital embodied in an experienced staff; (v) the MFI acquires a reputation as a serious organization capable of sustaining relationships with clients; and (vi) the MFI has likely established connections with international networks and enjoys the resulting technology transfers. All of the above represent benefits or sources of increased productivity over time for the MFI.

Thus, there are good reasons to expect MFIs that have been in operation longer to be able to reduce costs through learning by doing. However, there are also possible reasons why costs may be flat or even increasing with time, including the following factors: (i) screening and monitoring costs may rise as MFIs reach beyond their initial target group, (ii) operating costs may increase if MFIs move into more isolated and rural markets,(iii) operating costs could rise if MFIs begin competing in increasingly saturated markets, (iv) higher collection costs may be associated with a possible culture of nonrepayment and may be experienced if the MFI has to address increasing default rates, and (v) village banking methods may simply replicate costs as they are extended into new areas. Given the many potential differences in operating environments, degree of subsidization, organizational structure, and lending technology, it is not clear that any finding of increasing cost effectiveness would apply equally to all MFIs. It is for this reason that we estimate a mixture of cost functions along the lines of Beard, Caudill, and Gropper (1991, 1997).

Using the mixture estimation technique we find that there are, in fact, two distinct types of MFIs operating in this region during 2003 and 2004. About half of the MFIs are becoming more cost effective with time and about half are not. In order to determine which MFI characteristics are associated with decreasing costs and which are not, we estimate several auxiliary regressions. Cost reductions are found to be related to several factors. Importantly, lower total subsidies and a lower subsidy per loan are associated with greater cost reductions. MFIs offering deposits tended to improve over time, as did those located in Central Asia. Those MFIs not in networks also tended to achieve cost reductions.

Briefly, we find that the group of MFIs that is becoming more cost effective over time is relying less on subsidies and more heavily on deposits as a source of loanable funds. These MFIs are basically transforming themselves into institutions similar to small banks. A second group of MFIs is not showing increased cost effectiveness, and remains dependent on subsidies. To provide additional context for these findings, we turn next to prior research on MFIs, then present our model and data, and then discuss the results in detail.

1. PREVIOUS RESEARCH

Some of the research on microfinance has focused on the demand side of the market and specifically on the impact of microfinance on clients (see, e.g., McKernan

2002, Armendariz de Aghion and Morduch 2005, chap. 8, Karlan and Zinman 2008, Hartarska and Nadolnyak 2008). Studies on the supply side of microfinance have progressed from a focus on financial policies to a focus on lending technologies and, more recently, to organizational form (Adams Graham and von Pischke 1984, Gonzalez-Vega 1998, Hartarska and Holtmann 2006). Much of this research focuses on innovations in lending technologies, such as joint-liability contracts and dynamic incentives, which alleviate information asymmetries and decrease screening, monitoring, and contract enforcement costs (Stiglitz 1999, Ghatak and Guinnane 1999, Conning 1999, Armendariz de Aghion and Morduch 2000, Paxton and Thraen 2003, Jain and Mansuri 2003).

Studies that explore the productivity and efficiency of organizations providing microfinance are predominantly case studies describing the experience and performance of a single MFI or a group of MFIs operating in one country or in similar markets (e.g., Navajas and Gonzalez-Vega 2003, Hernandez-Trillo, Pagan, and Paxton 2005). In some of these studies, the role of subsidies has been of special interest because questions such as how much and how long to subsidize an MFI have important policy implications (Morduch 1999b). While learning by doing can be important for any organization, it is particularly important for MFIs because microfinance, at its core, is about fundamental innovation in lending practices and the development of new lending innovations largely through trial and error. Understanding the risks involved in microfinance may also be best accomplished through experience, as managers and loan officers learn about their borrowers and the lending technologies most effective to serve them. Further, the changing institutional environments in transitional economies require adaptation and learning over time, with each situation likely to provide its own challenges and opportunities. While it is useful to conduct case studies to gain insight into particular situations, it is also important to look at many institutions to make broad comparisons across the MFI population.

Empirical work on the efficiency and productivity of MFIs is scarce, largely because there are significant data limitations. Competition for donor funds between MFIs, however, has brought increased transparency that has, in turn, led to increased availability of data. More MFI data are becoming available through traditional sources like the *Microbanking Bulletin* (MBB) and the MIXMARKET Information Exchange, which now collects data from many more MFIs than in the 1990s. The *Microbanking Bulletin* averages performance ratios by geographic region and target market for organizations that choose to provide data. These ratios are widely used as benchmarks but have limitations. For example, Gutiérrez Nieto, Serrano Cinca, and Mar Molinero (2007) find that MFI performance rankings based on MBB ratios differ from rankings produced by nonparametric (DEA) efficiency analysis.

Newly available data, however, provide an opportunity to identify factors associated with successful MFIs. For example, Cull, Demirgüç-Kunt, and Morduch (2007) use MBB data from 2001 to study profitability and outreach of leading MFIs. They find that differences in institutional design and orientation matter. For example, they find that MFIs that focus on lending to individuals invest heavily in staff in order to protect their portfolios but those that emphasize group lending do not. Other research by Hartarska (2005) on MFIs in the ECA region finds that MFI board composition and managerial compensation affect the performance of MFIs. However, much remains to be learned about MFI operations and efficiency.

MFIs operating in Eastern Europe and Central Asia are somewhat different from MFIs operating elsewhere in the world. Compared to MFIs in other regions, the MFIs in the ECA region are among the youngest in the microfinance industry, while their performance ranks among the best (Berryman 2004). For example, *Microbanking Bulletin* No. 9 shows that in 2003, the average MFI in the ECA region was 5 years old, had gross portfolio yield of 35% (in real terms), and operational self-sustainability of 131%. The averages for the entire MFI industry are: 9 years old, gross portfolio yield of 29%, and operational self-sustainability of 123%.

In light of the distinctive nature of the MFIs in the ECA region and their marked success, and motivated by limits in the understanding of MFI costs, we undertake this study. We begin by estimating a cost function for MFIs in the ECA region.

2. THE MODEL

We estimate the cost function for MFIs using the translog (transcendental logarithmic) form for all estimations. While there are limitations to the translog form, it has a long history of use in the study of financial institutions (e.g., see Ferrier and Lovell 1990, Altunbas and Molyneaux 1996, DeYoung and Hasan 1998, Bonin, Hasan, and Wachtel 2005, Fries and Taci 2005). Importantly, it is also sufficiently parsimonious for use in the mixture procedure (Beard, Caudill, and Gropper 1997).

The translog functional form is given by:

$$\begin{aligned}\ln C = {} & \alpha_0 + \sum \alpha_j \ln q_j + \sum \beta_k \ln p_k + (1/2) \sum \sum \alpha_{ij} \ln q_i \ln q_j \\ & + (1/2) \sum \sum \beta_{lk} \ln p_l \ln p_k + \sum \sum \delta_{jk} \ln q_j \ln p_k, \qquad (1)\end{aligned}$$

where C is total cost, qs are output quantities, and ps are input prices. Homogeneity in input prices is imposed in the estimation by normalizing (dividing) all input prices and total cost by the price of capital (P_{CAP}).

3. A MIXTURE MODEL OF COST FUNCTIONS

To investigate the issue of whether there are two cost regimes in MFI operations, we employ the approach of Beard, Caudill, and Gropper (1991, 1997), who used mixture models in the estimation of cost functions. The strength of the mixture approach is that the traditional assumption that all institutions are drawn from a single underlying distribution is actually a testable hypothesis. One does not need prior information about whether there are two regimes; the data and the estimation reveal whether there are distinct groups of institutions, and which MFIs are most similar from a statistical cost function standpoint. If the test for the existence of two regimes is rejected, the estimated model becomes the traditional model; thus, the mixture approach is a more general form of the traditional single cost function. If the mixture estimation indicates the existence of two underlying distributions, then second-stage auxiliary regressions can be used to further examine the nature of the two probabilistically determined regimes. Some other applications of mixture models in interesting contexts in economics and finance include Asquith, Jones, and Kieschnick (1998), Conway and Deb (2005), Lindemann, Dunis, and Lisboa (2004), Sjoquist, Walker, and Wallace (2005), and Yoo (2005).

For several reasons the mixture approach may prove useful in an examination of the cost structure of MFIs. Though all MFIs are similar, there are many observable differences in MFIs that might affect production costs. MFIs operate in many different countries and environments under very different restrictions and regulations. Also, MFI charters differ, insofar as MFIs can be chartered as banks, credit unions, nonbank financial institutions, or nongovernmental financial institutions. Some MFIs claim to be operating as profit-maximizing entities, while others are nonprofit organizations, and some MFIs operate as part of a larger international network. Some MFIs are heavily subsidized, whereas others are not. These differences are all measurable and, if desired, could be used either to separate the sample or to be directly incorporated into the estimation. In contrast, the mixture procedure allows the sample to be probabilistically separated based on unobservable factors. If the mixture estimation procedure finds two groups of MFIs associated with different cost functions, we can then examine the MFIs assigned to each regime in order to search for common characteristics.

4. ESTIMATION OF A MIXTURE MODEL BY THE EM ALGORITHM

Following Quandt (1988), we illustrate the expectation-maximization (EM) algorithm for the case of a mixture of two normal regressions (or switching regressions), consider

$$\begin{aligned} Y_i &= X_i\beta_1 + \varepsilon_{1i} \text{ with probability } \theta \\ Y_i &= X_i\beta_2 + \varepsilon_{2i} \text{ with probability } 1-\theta, \end{aligned} \tag{2}$$

where ε_{1i} and ε_{2i} are mutually independent, i.i.d. normal with zero means, and variances σ_2^1 and σ_2^2, respectively. In this case the incomplete, or observed, data likelihood is given by

$$f(Y_i) = \frac{\theta}{\sqrt{2\pi}\sigma_1}\exp\left\{-\frac{(Y_i - X_i\beta_1)^2}{2\sigma_1^2}\right\} + \frac{1-\theta}{\sqrt{2\pi}\sigma_2}\exp\left\{-\frac{(Y_i - X_i\beta_2)^2}{2\sigma_2^2}\right\}. \tag{3}$$

To write the complete-data likelihood, define the indicator variable d_{ij} where $d_{i1} = 1$ if the observation is associated with the first component, 0 otherwise, and $d_{i2} = 1$ (in our two-component case, really $1-d_{i1}=1$) if the observation is associated with the second component, 0 otherwise. The extension of this definition of d to more than two components is obvious. The problem for estimation is that d is not observed. If d were observed, the sample could be partitioned and separate regressions estimated for each component, but if d is unknown it must be considered a random variable. Specifically, in our two-component case, d is a Bernoulli trial with probability 2. Thus, the typical complete-data density function is given by

$$f(Y_i) = \left\{\frac{\theta}{\sqrt{2\pi}\sigma_1}\exp\left\{-\frac{(Y_i - X_i\beta_1)^2}{2\sigma_1^2}\right\}\right\}^{d_{i1}} \times \left\{\frac{1-\theta}{\sqrt{2\pi}\sigma_2}\exp\left\{-\frac{(Y_i - X_i\beta_2)^2}{2\sigma_2^2}\right\}\right\}^{1-d_{i1}}. \tag{4}$$

These densities comprise the logarithm of the complete-data likelihood function that is given by

$$\ln L = \sum_{i=1}^{n}\{d_{i1}(\ln\theta + \ln f_{i1}) + (1-d_{i1})(\ln(1-\theta) + \ln f_{i2})\}, \tag{5}$$

where f_{i1} and f_{i2} are the respective normal density functions.

In the E step of the EM algorithm, the expected value of the log likelihood is needed, which requires replacing d by its expectation given the data. This expectation is given by $E(d_{i1}|Y_i) = (1)[(P(d_{i1}=1|Y_i)] + (0)[P(d_{i1}=0|Y_i)] = P(d_{i1}=1|Y_i)$. This expected value or probability can be evaluated by using Bayes' rule that, when applied to $E(d_{i1}|Y_i)$ yields

$$P(d_{i1}=1|Y_i) = \frac{P(d_{i1}=1)P(Y_i|d_{i1}=1)}{\sum_{i=1}^{2}P(d_{ij}=1)P(Y_i|d_{ij}=1)} = \frac{\theta f_{i1}}{\theta f_{i1} + (1-\theta)f_{i2}} = w_{i1}. \tag{6}$$

Evaluation of (6) provides estimates of the expected values or probabilities or weights, w_{i1} and $1-w_{i1}$. Once these weights have been calculated, they can be substituted into the log of the complete-data likelihood that is then maximized in the M step of the EM algorithm with respect to the unknown parameters in the model.

To examine the M step of the EM algorithm, return to the log of the complete data likelihood, and substitute for $E(d_{i1})$ to yield

$$E(\ln L) = \sum_{i=1}^{n}\{w_{i1}(\ln\theta + \ln f_{i1}) + (1-w_{i1})(\ln(1-\theta) + \ln f_{i2})\}. \tag{7}$$

Let X denote the matrix containing the independent variables, Y denote the vector containing the dependent variable, and let W_1 and W_2 be given by

$$W_1 = \mathrm{diag}[w_{11}, w_{12}, \ldots, w_{n1}] \quad \text{and} \quad W_2 = \mathrm{diag}[w_{21}, w_{22}, \ldots, w_{2n}]. \tag{8}$$

Clearly, $w_{i1} = 1 - w_{i2}$, for all I, so $W_1 = I_n - W_2$. Differentiating the expected log-likelihood function and solving yields

$$\begin{aligned}
\hat{\beta}_1 &= (X'W_1X)X'W_1Y \\
\hat{\beta}_2 &= (X'W_2X)X'W_2Y \\
\hat{\sigma}_1^2 &= \frac{1}{\sum_{i=1}^{n} w_{i1}} \sum_{i=1}^{n} w_{i1}(Y_i - X_i\hat{\beta}_1)^2 \\
\hat{\sigma}_2^2 &= \frac{1}{\sum_{i=1}^{n} (1 - w_{i1})} \sum_{i=1}^{n} (1 - w_{i1})(Y_i - X_i\hat{\beta}_2)^2 \\
\hat{\theta} &= \sum_{i=1}^{n} w_{i1}.
\end{aligned} \tag{9}$$

These solutions are the familiar weighted least squares (WLS) expressions for the regression parameters in the case of maximum likelihood estimation via the EM algorithm. Given starting values, this algorithm can be used to generate a convergent sequence of parameter estimates.

5. DATA

An important advantage of this study is the use of high-quality MFI data that have recently become available. This data set overcomes some of the limitations of using MFI financial statements. The use of financial statements from various MFIs makes comparisons problematic because MFIs are organizationally diverse and are regulated differently so that the financial reporting standards are not necessarily consistent. For example, their financial statements might not include all subsidies and dollar amounts might not be inflation adjusted. Auditing of financial statements is not required of all organizational types. Moreover, differences in cross-country accounting standards complicate the comparison of financial statements across countries.

To correct for such problems, the MBB has developed standards that facilitate comparisons of MFI financial statements across countries. Individual MFIs from across the world submit their financial data, which is checked and corrected by the MBB staff or a regional partner. The data used in this study were checked and corrected by the staff of the Microfinance Center for Central and Eastern Europe and the Newly Independent States (Microfinance Center for CEE & NIS). Our data set includes not only the MFIs that reported to the MBB but also all MFIs reporting to the Microfinance Center for CEE & NIS. The standardizing process involved examining each individual MFI financial statement, performing numerous checks and, when necessary, collecting follow-up data to ensure consistent adjustments for inflation and subsidy so that data across MFIs are comparable. These corrected data are used here.

TABLE 1

Geographic Distribution of Sample of Microfinance Institutions

Country	Number of observations
Albania	6
Armenia	9
Azerbaijan[a]	7
Bosnia and Herzegovina	25
Bulgaria	6
Croatia	4
Georgia[a]	15
Kazakhstan[a]	4
Kosovo	6
Kyrgyzstan[a]	5
Macedonia	1
Moldova	1
Mongolia[a]	3
Montenegro	3
Poland	1
Romania	10
Russia	20
Tajikistan[a]	3
Ukraine	3
Uzbekistan[a]	2
Yugoslavia	3

[a]Those countries included in the *CENTRALASIA* variable are designated above.

Our data set contains financial information on MFIs operating in Eastern Europe and Central Asia for the years 2003 and 2004. Such high-quality data are not available for a longer time period because MBB does not disclose individual MFI data, and collaboration between MBB and the Microfinance Center for CEE & NIS was not continued after 2004. The geographic distribution of the MFIs in our sample is given in Table 1.

Our selection and specification of regression variables generally follows LeCompte and Smith (1990) and Caudill, Ford, and Gropper (1995). All financial variables are denominated in U.S. dollars and adjusted for country-specific inflation. The input prices for financial and physical capital faced by MFIs in the sample may be subsidized to varying degrees, through donations of physical or financial capital, or through provision of loanable funds at concessional interest rates. We use the actual input prices faced by managers in the cost function.

In this study we consider lending services to be the output of the MFI, which are measured by both the number of borrowers served and the volume of loans. We use three inputs in our cost model: labor, physical capital, and financial capital. In the auxiliary regressions, we examine other variables that may be associated with the different cost regimes, including firm-specific and environmental variables. A brief discussion of the construction of each of the variables used in this study follows.

Labor. The price of labor is calculated as actual personnel expense divided by the number of employees.

Physical capital. The price of physical capital is calculated as actual operating expense minus actual personnel expense divided by the net fixed assets (i.e., fixed assets net of accumulated depreciation and adjusted for inflation to account for appreciation of the physical assets).

Financial capital. The price of financial capital is calculated as the actual expense on financial capital divided by the stock of financial capital. Financial expense is calculated as the sum of interest and fees on all borrowing and deposits, net of inflation adjustment expense (calculated as the difference between inflation adjustment expense, due to inflation eroding the portfolio, and inflation revenue, resulting from the increased value of fixed assets) plus other financial expense, including exchange-rate-related expense.

Exchange rate expense is included in calculating the price of financial capital because many MFIs obtain loans in hard currency (U.S. dollars or euro) but extend loans in local currency and thus incur opportunity costs as well as actual exchange rate expenses and risk. Since the actual price that managers face is used as the price of financial capital, interest rate subsidies are not included in the calculation of the price of capital. These subsidies are included in the measurement of the total subsidy, together with the cost of donated equity (proxied by the deposit rate, and all in-kind subsidies).

Output. We use two measures of lending output: one is the number of borrowers served and the other is the volume of loans made. The data on MFIs contain number of borrowers and not number of loans, but previous work indicates that a very close association between the number of borrowers and number of loans exists for MFIs in this region (Hartarska 2005). In a preliminary analysis we used only the number of borrowers served as our measure of lending output, with results very similar to those reported here. Although one goal of MFIs is to service the largest number of borrowers with small loans, production costs are also affected by the volume of loans. As a result, we include the dollar volume of loans as another measure of lending production to take into account differences in loan volume across institutions.

Total cost. Total cost is the sum of input quantities times input prices.

Age. We include the age of the institution. As noted earlier, we expect that learning occurs over the life of the MFI as managers gain information and experience in that particular institution and economic environment. Given the lack of formal credit histories for many borrowers and the importance of learning about these borrowers that can only occur with time, we expect older MFIs to become more effective producers, so that costs are lower for a given amount of lending output.

Estimation of the statistical cost function provides a solid theoretical framework in which to evaluate a variety of factors related to MFI performance. The cost function is estimated as a function of input prices and output quantities, with a single exogenous variable, *AGE,* incorporated directly into the cost function. We then estimate a mixture model to test whether there are two significantly different cost regimes apparent in these data and, if so, examine the characteristics of the MFIs associated with the different regimes. If needed, this comparison will be facilitated by the estimation of several auxiliary regressions.

If needed, several groups of explanatory variables can be used to identify the characteristics of MFIs associated with each regime. These include characteristics of the institution, such as their lending practices, their portfolio compositions, and organizational structures, as well as the different economic environments in which they operate. Variables providing information about each of these characteristics and situations are discussed below.

The first group includes variables measuring different deposit-taking and lending practices. These include a dummy variable equal to one if the MFI takes deposits (*DDEPOSITS*), as well as a variable showing the volume of deposits (*VOLDEPOSITS*). In addition, a dummy variable (*GROUP*) is set equal to one if the MFI offers only group loans through village banking or solidarity groups, a potentially important distinction for MFIs (see Giné and Karlan 2006, Ahlin and Townsend 2007). The average loan balance (*AVGLN*) is also a possibility. Other possibilities are two variables measuring characteristics of the lending client base; the percentage of women borrowers (*PCT_WOMEN*) and the percentage of rural clients (*PCT_RURAL*) that are available for a subgroup of the data.

The second group of variables captures differences in organizational types: a dummy variable indicating that the MFI belongs to a network (*DNETWORK*), the number of employees (*NUEMPL*), a dummy variable indicating that the MFI is a nongovernmental organization (*NGO*), and a dummy variable indicating the MFI is a bank (*BANK*).

In addition, the external economic environment may be a critical factor affecting MFI operations. We have available GNP per capita (*GNPCAP*), the growth rate of GDP (*GDPGROWTH*), and a measure of financial depth in the country (*FINDEPTH*), which is measured as liquid liabilities (M3) as a percentage of GDP. A dummy variable equal to one if the MFI is located in Central Asia (*CENTRALASIA*) is also available.

One interesting variable available for use in the auxiliary regressions is a measure of subsidy. Our constructed subsidy variable (*SUBSIDY*) is the sum of two components. The first component accounts for in-kind payments that subsidize the costs of labor and physical capital, and is calculated as the difference between adjusted and unadjusted operating expense. The second component is the opportunity cost of subsidized financial capital calculated as the deposit rate times the average equity, which is the sum of beginning-of-the-year and end-of-year equity (which includes current-year direct subsidies) divided by two. We also have available subsidy per loan (*SUBNLOAN*) and subsidy per dollar of loans (*SUBVLOAN*) as measures of subsidy, which provides an adjustment for the size of the MFI.

Variables that reflect portfolio risk include loans overdue more than 30 days (*PAR30*), write-off ratio (*WRITEOFF*), and capital-to-asset ratio (*CAPASSR*). We also have two measures of MFI size: total assets (*TA*) and total equity (*TE*), all adjusted for inflation and subsidy. Summary statistics for all variables used in this analysis are given in Table 2.

TABLE 2

Summary Statistics for the Microfinance Institutions Data Set

Variable	Mean	Standard deviation	Minimum	Maximum
Adj. Total Assets	22,271,893.3	63,824,478.7	61,647.0	472,120,064.0
Total Cost	2,874,860	6,802,379	8,789	54,131,392
Nloan	7,131.48	7,933.85	66.0	36,730.0
VLoan	15,086,577.5	38,182,726.1	30,397.3	249,674,592.0
P_L	9,168.52	5,553.87	694.44	26,728.13
P_K	5.30	10.47	0.12	68.90
P_{CAP}	0.067	0.053	0.003	0.31
AGE	5.57	2.04	1.00	12.0
GROUP	0.06	0.24	0	1.0
DDEPOSITS	0.65	0.47	0	1.0
PCT_WOMEN[a]	0.61	0.24	0.05	1.0
PCT_RURAL[b]	0.35	0.26	0	1.0
BANK	0.14	0.35	0	1.0
NGO	0.34	0.48	0	1.0
DNETWORK	0.70	0.46	0	1.0
NUEMPL	111.1	180.9	3	1,045
PAR30	0.020	0.032	0	0.191
WRITEOFF	0.017	0.051	0	0.537
SUBNLOAN	72.63	111.74	0	852.23
SUBVLOAN	0.050	0.050	0	0.329
SUBSIDY	332,790.1	669,837.9	0	5,534,450.5
CENTRALASIA	0.29	0.45	0	1.0
GNPCAP	1,884.1	1,153.3	190.0	6,590.0
GDPGROWTH	0.066	0.032	−0.005	0.139
FINDEPTH	0.27	0.19	0	0.68

Note: There were 137 observations in the complete data set.
[a,b] Statistics for these variables are based on only 123 and 95 observations, respectively, due to missing values.

6. ESTIMATION RESULTS

The estimation results are contained in Table 3. We estimate both the usual ordinary least squares (OLS) regression model and the normal mixture model. The OLS estimation results are contained in column 2 of Table 3. The model R^2 is 0.975, which is high considering the many differences in MFIs operating in the ECA region. Of the 16 coefficients in the model, 11 are statistically significant at the $\alpha = 0.10$ level or better. The coefficients of *NLoan* and *VLoan* are both statistically significant and positive. The coefficient of the price of labor is positive and statistically significant. The coefficient on the price of capital is positive but not statistically significant. The key coefficient of *AGE* is negative and statistically significant, indicating that MFI costs decline with time. This result suggests that MFI managers are learning over time, which is essential to improved MFI operations. To determine whether all MFIs are improving over time, we turn to the estimation of the mixture model.

The results of estimating the mixture model are contained in columns 3 and 4 of Table 3. A modified chi-square statistic, called the Wolfe test (Wolfe 1971) can be used to test for the presence of a mixture against the null of a single regime (the traditional model). In our case the Wolfe statistic is 68.65, indicating the presence of

TABLE 3

OLS and Mixture Regression Results

Variable	OLS results	Mixture results regime 1	Mixture results regime 2
Intercept	0.610**	0.322*	0.815**
	(6.28)	(2.17)	(11.14)
NLoan	0.386**	−0.114	0.563**
	(5.73)	(0.77)	(8.93)
VLoan	0.588**	0.816**	0.507**
	(10.77)	(6.44)	(11.44)
P_L	0.404**	0.294*	0.530**
	(7.10)	(2.20)	(12.08)
P_K	0.030	−0.113	0.142**
	(0.78)	(1.17)	(4.15)
*NLoan***NLoan*	0.104	−0.016	0.195**
	(1.87)	(0.14)	(3.79)
*VLoan***VLoan*	0.002	0.292*	−0.129**
	(0.03)	(2.14)	(3.21)
*Nloan***Vloan*	−0.009	−0.225	0.053
	(0.16)	(1.74)	(1.15)
$P_L{}^* P_L$	−0.035	0.184	−0.189**
	(0.73)	(1.65)	(4.42)
$P_K{}^* P_K$	−0.112**	−0.074	−0.071*
	(4.23)	(1.40)	(2.70)
$P_L{}^* P_K$	0.064*	0.094	0.102**
	(2.48)	(1.70)	(4.77)
$P_L{}^*$*VLoan*	−0.008	−0.026	0.080**
	(0.21)	(0.28)	(2.96)
$P_K{}^*$*VLoan*	−0.056*	−0.128	−0.013
	(2.14)	(1.73)	(0.66)
$P_L{}^*$ *NLoan*	−0.060	0.039	−0.096**
	(1.67)	(0.58)	(3.19)
$P_K{}^*$ *NLoan*	0.062*	0.074	0.011
	(2.24)	(1.34)	(0.39)
AGE	−0.040*	−0.011	−0.068**
	(2.95)	(0.72)	(6.77)
Σ	0.288	0.202	0.093
Θ	—	0.505	0.495
R^2	0.975	—	—
F	312.37	—	—

Note: Regime 2 is the regime where the age of the MFI is associated with significantly reduced costs; we, therefore, refer to it as the "more cost effective" regime, while regime 1, which shows no significant reduction in costs with age, is referred to as the "not more cost effective" regime.

[a]Numbers in parentheses are absolute values of *t*-ratios.

* and ** indicate statistical significance at the $\alpha = 5\%$ and 1% levels, respectively.

two regimes. More evidence in support of the existence of two regimes can be seen by examining the standard errors of the regression for the two regimes in comparison with the standard error in the OLS regression model. The estimated standard error of the first regime is 0.20 and the estimated standard error of the second regime is 0.09. Note that both of these values are smaller than their OLS counterpart, which is 0.29. This relationship suggests that two regression regimes exist and that the mixture procedure is not simply "creamskimming," or just putting the outliers in one regime and those observations on or near the regression line in the other regime. The estimated mixing parameter (shown by θ in Table 3) indicates that about one-half of the observations are associated with regime 1 (50.5%) and about one-half (49.5%) with regime 2.

The mixture results from the estimation of the first regime are contained in column 3 of Table 3. Eight of the 16 coefficients are statistically different from zero at the $\alpha = 0.10$ level or better. Compared to the OLS results, the coefficient of *NLoan* is negative and no longer statistically significant, the coefficient of *VLoan* remains statistically significant, and the coefficient of the price of capital is negative but not statistically significant. The coefficient of *AGE* is no longer statistically significantly different from zero, although the sign remains negative. This regime characterizes one-half of the sample and for these MFIs there appears to be no significant improvement in cost effectiveness over time.

The mixture results from estimating the second regime are given in column 4 of Table 3. Thirteen of the 16 coefficients are significantly different from zero at the $\alpha = 0.10$ level or better. The input price coefficients in this regime are well behaved, both positive, summing to less than one, and achieving statistical significance. In this regime the negative coefficient of *AGE* indicates that these MFIs, constituting one-half of the sample, are becoming more cost effective over time. This result stands in contrast to our finding for the MFIs associated with regime 1. Thus, the mixture model reveals that about half of the MFIs are operating with reduced costs over time and half are not. To improve the clarity of the following discussion for the reader, from here on we generally refer to regime 2, which is associated with reduced costs with institution age, as "*more cost effective*" and we refer to regime 1, which is associated with no change in costs with age, as "*not more cost effective.*"

One interesting distinction between the estimation results for the two regimes is apparent in the differences in the estimates of the coefficient of the variable, *NLoan*. For regime 1, the coefficient of the variable *NLoan* is equal to -0.114 and is not statistically significant. The results are much different in regime 2, where the coefficient of the variable, *NLoan*, is equal to 0.563 and is significant. This statistically significant relationship may indicate that the MFIs associated with regime 2 are participating to a much greater degree in monitoring and enforcement of loans and repayment thereof.

In order to investigate the characteristics of those MFIs associated with each different regime in the mixture model, we turn next to the estimation of a set of auxiliary regressions that include firm-specific and environmental variables discussed previously. An outcome of the estimation of a mixture model is that one obtains an estimate of the posterior probability that an observation comes from either regime. In the auxiliary regressions we report in Table 4, the dependent variable is the posterior probability that an MFI is associated with regime 2, the more-cost-effective regime. We begin the estimation of the auxiliary regression with the large group of characteristics described in the data section; we allow the procedure to admit those characteristics most useful in explaining the probability of an MFI being associated with regime 2. Since there is no precise theoretical model that indicates which measures should be included and which should not, we utilize several alternative specifications. In an effort to explain as much of the variation in the probability of regime membership, we use two different regression search procedures: a stepwise regression procedure and a maximum R^2 search procedure.

TABLE 4

AUXILIARY REGRESSIONS FOR THE PROBABILITY OF MEMBERSHIP IN THE MORE-COST-EFFECTIVE REGIME

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	0.737**	0.712**	0.761**	0.706**
	(9.11)	(8.67)	(8.57)	(8.29)
DNETWORK	−0.212**	−0.209**	−0.212**	−0.198**
	(2.88)	(2.84)	(2.90)	(2.73)
VOLDEPOSITS	0.013	0.014	0.012	—
	(1.78)	(1.84)	(1.65)	
CENTRALASIA	0.148*	0.135	0.152*	0.175*
	(1.98)	(1.81)	(2.01)	(2.21)
GROUP	—	0.209	0.263	0.228
		(1.46)	(1.78)	(1.57)
NGO	—	—	−0.426	—
			(1.41)	
SUBNLOAN	—	—	—	−0.0007*
				(1.96)
AVGLN	—	—	—	0.00005*
				(2.19)
R^2	0.092	0.107	0.120	0.123
F	4.51**	3.95**	3.58**	3.68**
Obs.	137	137	137	137

NOTE: *VOLDEPOSITS* in tens of millions of U.S. dollars.
[a]Numbers in parentheses are absolute values of t-ratios.
* and ** indicate statistical significance at the $\alpha = 5\%$ and 1% levels, respectively.

6.1 Auxiliary Regression Estimation Results

The results from estimating these auxiliary regressions are contained in Table 4. Four models are presented. The first three are the results of using a stepwise procedure and the fourth is the result of a maximum R^2 search. The results from estimating model 1 are given in column 1 of Table 4. This model is the result of using the stepwise procedure to admit three explanatory variables to explain the probability of membership in regime 2. The model contains *DNETWORK*, *VOLDEPOSITS*, and *CENTRALASIA* as explanatory variables. All of the coefficients of these variables are statistically significant at the $\alpha = 0.10$ level or better. The signs of these estimated coefficients tell an interesting story. Those MFIs that belong to networks are most closely associated with regime 1. A network may provide a safety net for MFIs as a possible source of subsidies and hence reduce the incentives for self-sufficiency. The positive coefficient on *VOLDEPOSITS* indicates that increases in deposits are associated with MFIs improving over time. This result is unsurprising; MFIs with sizable deposits may be well on their way to becoming self-sufficient (if they are not already) and is consistent with Hartarska and Nadolnyak (2007), who found that deposit-taking institutions reach more borrowers. The final coefficient is that of the *CENTRALASIA* dummy variable, indicating that MFIs in Asia are improving more over time than their Eastern European counterparts.

Column 3 of Table 4 shows the best model containing four independent variables as determined by the stepwise procedure. This model is the same as the previous model but the *GROUP* dummy variable is added. All of the coefficients of these variables except *GROUP* are statistically significant at the $\alpha = 0.10$ level or better. The signs of the coefficients of *DNETWORK, VOLDEPOSITS,* and *CENTRALASIA* are the same as before. The coefficient of the *GROUP* variable, indicating the presence of either village banking or membership in a solidarity group and that the MFI offers only group loans, is positive, indicating that MFIs using these lending technologies are improving over time.

The search results for the best five-variable model are shown as model 3 in Table 4. This model includes *DNETWORK*, *VOLDEPOSITS*, *CENTRALASIA*, *GROUP*, and *NGO*. All of the coefficients of these variables except *NGO* are statistically significant at the $\alpha = 0.10$ level or better. The signs of *DNETWORK*, *VOLDEPOSITS, CENTRALASIA,* and *GROUP* are consistent with our earlier models, so we turn our attention to the new variable in the model, NGO. Although not statistically significant, the negative coefficient indicates NGOs are more likely to be members of regime 1.

The results from estimating the final model are given in column 5 of Table 4. These results are obtained from a search procedure in which the model with the highest R^2 is preferred. We present the results for the best model with five independent variables. This model includes three variables familiar from our previous search procedure: *DNETWORK*, *CENTRALASIA*, and *GROUP*. All of the coefficients of these variables except *GROUP* are statistically significant at the $\alpha = 0.10$ level or better, and the signs and magnitudes are consistent with our previous findings. The new variables inserted by this procedure include the total *SUBNLOAN*, and average loan balance, *AVGLN*. The coefficient of *SUBNLOAN* is negative and statistically significant, indicating that the MFIs with larger subsidies per loan are less likely to be in the regime with the greater cost savings. This result is unsurprising and, again, can be considered consistent with a reduced incentive for internal efficiency, or at least that larger subsidies alleviate some pressure to realize cost reductions. The sign on *AVGLN* indicates that higher values of the average loan balance are associated with regime 2. This may indicate that it is easier to reduce costs if the MFI is making larger size loans. Put differently, MFIs that make smaller loans may find it more difficult to reduce costs over time.

These findings seem logical. Subsidies may reduce the incentives to pursue cost efficiency, and network memberships may do the same, as they give members easier access to subsidies. The presence of deposits can be important for MFIs and indicates that an important step toward sustainability has been taken. Deposits may also indicate a maturing client base, with better credit and repayment practices, and stronger formal financial histories.

Other auxiliary regression models were estimated to investigate whether macroeconomic and demographic variables such as per capita income, population density, economic growth rates, or financial depth helped explain cost regime membership, particularly since the *CENTRALASIA* variable is consistently statistically significant. However, in none of these regressions were these variables found to be statistically significant. Several additional auxiliary regression models were also estimated in an attempt to investigate whether the client composition variables *PCT_WOMEN* or

TABLE 5

MEANS OF SELECTED VARIABLES FOR MFIs WITH 20 HIGHEST POSTERIOR PROBABILITIES OF ASSOCIATION WITH EACH REGIME

Variable	Regime 1 (not more cost effective)	Regime 2 (more cost effective)	Percent change (regime 2 vs. regime 1)
Lending and deposit-taking practices			
DDEPOSITS	0.550	0.850	54.55
VOLDEPOSITS	4,993	23,668,170	473,927.04
GROUP	0	0.150	Undefined
AVGLN	2,150.0	2,011.8	−6.43
PCT_WOMEN[a]	62.0%	64.8%	4.52%
PCT_RURAL[b]	21.7%	49.6%	128.57%
Organizational structure			
DNETWORK	0.850	0.250	−70.59
NUEMPL	67.20	84.75	26.12
NGO	0.600	0.300	−50.00
BANK	0.100	0.100	0.00
Economic environment			
CENTRALASIA	0.150	0.400	166.67
FINDEPTH	0.234	0.215	−8.112
GNPCAP	2,070.1	1,970.85	−4.79
GDPGROWTH	7.23%	7.75%	7.19
Subsidy measures			
SUBSIDY (total)	239,657	133,681	−44.22
SUBNLOAN	139.72	52.81	−62.20
SUBVLOAN	0.070	0.047	−32.85
Donated Equity	2,117,214	289,071	−86.35
Subsidized Borrowing	556,065	31,205	−94.39
Portfolio measures, including risk			
PAR30	0.023	0.018	−21.74
WRITEOFF	0.016	0.038	137.50
CAPASSR	0.731	0.476	−34.88
Adj. Total Equity	3,504,967	2,332,318	−33.46
Adj. Total Assets	5,531,222	31,584,418	471.02

[a]This variable has missing values. The mean for regime 1 is based on 19 observations and the mean for regime 2 is based on 18 observations.
[b]This variable has missing values. The mean for regime 1 is based on 16 observations and the mean for regime 2 is based on nine observations.

PCT_RURAL helped explain group membership for these MFIs; in no case were these two variables statistically significant. However, including these client variables also reduces the number of observations that can be included in the regressions by approximately 10% and 30%, respectively. These additional results are available from the authors upon request.

6.2 *Direct Data Comparisons*

Since there is a high degree of collinearity among the different variables, we also conduct a more direct comparison of the data, as shown in Table 5. More evidence on the nature of these two regimes can be determined by examining the MFIs classified into the different regimes using the posterior probabilities from the mixture model. We use the MFIs with the 20 highest predicted probabilities of membership in regime 2 and compare their characteristics to those MFIs with the highest predicted probabilities of membership in regime 1. This process should yield the MFIs most closely associated with each regime. The picture that is revealed supports and extends our auxiliary regression results on the nature of these two groups of MFIs.

The values for the two deposit variables differ dramatically for the two regimes. Eighty-five percent of the MFIs in regime 2 have some deposits, compared to 55% in the other regime, and the volume of deposits in regime 2, at more than US$23 million, is much larger than in regime 1, which has only slightly under US$5,000. Some interesting differences appear in the lending and client aspects as well. Fifteen percent of MFIs in regime 2 specialize completely in group lending, while none of those in regime 1 do. The percentage of women clients is slightly higher for regime 2, as is the percentage of rural clients; however, these last two measures were missing for some MFIs. The average loan size did not differ much between the two regimes; they were within 15% of each other.

In comparing the organizations of the MFIs and the economic environments in which they operate, 85% of regime 1 MFIs were in networks, compared to only 25% of regime 2 MFIs. In addition, in regime 1, 60% were NGOs and 10% were banks, while in regime 2, only 30% were NGOs and 10% were banks. Geographically, 40% of the MFIs in regime 2 were in Central Asia, while 15% of the regime 1 MFIs were in Central Asia. There were only slight differences in economic growth rates, in GNP per capita, and financial depth for the two groups.

Subsidies for regime 2 MFIs were invariably much smaller than those for regime 1. This pattern holds if we examine total subsidies, subsidies per loan, or subsidies per dollar of loans as well as some components of the subsidies, such as borrowing at subsidized rates; they are all less for regime 2 than for the other regime. Perhaps the not-more-cost-effective MFIs get those subsidies because their donors recognize that they cannot reduce costs further and operate without subsidies; but the more-cost-effective institutions appear to be able to reduce costs and reduce their dependence on subsidies. When examining the other portfolio measures, more-cost-effective MFIs have larger loan write-offs at 3.8% as compared to 1.6% in regime 1. More-cost-effective MFIs are also substantially larger than the other MFIs in total assets, and they are more leveraged, with less total equity and lower adjusted capital asset ratios.

In conclusion, two of the most important differences in Table 5 are the means of the variables *VOLDEPOSITS* and *Total Assets*. For example, more-cost-effective MFIs have several thousand times the volume of deposits as MFIs in the other regime. Also, MFIs in the more-cost-effective regime have more than five times the *Total Assets* of MFIs associated with the other regime. The differences in the means for these two variables suggest that those MFIs associated with the increasingly productive regime are much larger and much more heavily involved with demand and time deposits (as well as loans) than are their counterparts in the other regime. This finding is consistent with the possible cost savings due to the advantages afforded by potential economies of scale, as well as potential scope economies between deposits and loans. The size effect, in particular, may be an indicator of recent rapid growth suggesting that the productivity “gap” between the two groups of MFIs may continue to grow.

7. SUMMARY AND CONCLUSIONS

In this paper we use a cost function, including an institutional age variable, to determine whether MFIs in the ECA region are becoming more cost effective over time. Our empirical results do indicate that MFIs generally operate at lower costs over time. However, given the myriad differences in operating environments, degree of subsidization, and organizational form, we test the underlying assumption that all MFIs are adequately characterized by a single cost regime using a mixture model. We find two distinct types of MFIs operating in the ECA region; about half of the MFIs in the region are becoming more cost effective over time and about half are showing no improvement. Cost reductions are found to be related to several factors. Lower subsidies and lower subsidy per loan are associated with cost improvements. The MFIs relying more heavily on deposits also appear to be improving over time. Those MFIs that were not in networks tended to improve. MFIs located in Central Asia were more likely to improve than those in Eastern Europe. The reasons for these geographic differences did not appear to be adequately explained by differences in population density, economic growth rates, or other economic measures; they remain a question for future research.

Essentially, we find one group of MFIs that is becoming more cost effective over time—less reliant on subsidies and more reliant on deposits. A second group of MFIs, the one that is more heavily subsidized, remains dependent on those subsidies. The mixture methodology highlights the differences in conclusions that might be reached if one assumes that all MFIs are characterized by a single cost regime, since that approach found a statistically significant and negative association between organization age and costs for all MFIs taken as a single group. These findings contribute new evidence to the ongoing study of microfinance organizations and performance improvement, and highlight those factors associated with the institutions that were most effective at reducing costs over time. These findings also raise questions deserving further investigation, including the differences in performance between MFIs in different regions and countries, the measurement of possible economies of scale and scope for MFIs, and the precise mechanisms for the interaction between subsidies and efficiency of operations in individual MFIs.

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