Scale Economies in MFIs Abroad and Comparable U.S. Financial Institutions

by

Natalie Caroline James

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
May 14, 2010

Keywords: Microfinance, Efficiency, Non-stochastic production function, Elasticities, U.S. Community Development Banks, TARP

Approved by

Valentina Hartarska, Chair, Associate Professor of Agricultural Economics and Rural Sociology
James Barth, Professor of Finance
Henry Thompson, Professor of Agricultural Economics and Rural Sociology
Daniel Gropper, Professor of Economics

Abstract

The three essays of this dissertation employ a system of seemingly unrelated equations, each with a cost function and production input equations to determine the scale or point of production along the long-run average total cost curve for two samples of microfinance institutions and for a sample of U.S. Community Development Banks. Each essay is unique in its discovery. The first essay determines the scale of a large global sample of rated MFIs to be less than one and concludes that physical capital is an elastic input for production. The second essay explores the efficiency of MFIs by their organizational types and finds that NGOs (non-profits) are more efficient than regulated rural banks and non-bank financial institutions suggesting that non-profits may be in a better position to meet the needs of the poor. Eastern European MFIs are found to produce at their optimal scale while more growth opportunity lies with the African and South Asian MFIs. The third essay uses a 2 output (Loans and NII, non-interest income), 4 input[1] model to determine the effect of off-balance sheet activity on efficiency. The TARP distributions are noted and evidence is documented on current pay back of TARP funds by these institutions. There does not appear to be a strong relationship between TARP funds received and production cost.

[1] financial capital[1], labor, physical capital, and other borrowed money, including mortgage indebtedness, obligations under capitalized leases, federal funds purchased, and securities sold under agreements to repurchase

Acknowledgments

I am grateful to my parents, for their endless years of hard work that has supported my dream of higher education that many people aspire to do but can not because of financial and family constraints. I am thankful for the support of Dr. James Barth, Dr. Henry Thompson, and Dr. Valentina Hartarska. I also want to thank Dr. Jackson and Dr. Saba for their substantial effort with the Master's thesis, and Dr. Beard who consistently answered questions for the prelim insisting that I understand Microeconomics. I hope that the work of this dissertation, my master's thesis, my coursework, and the many hours that I spent in preparation to teach helps grant me the career path that will enable me to excel and will utilize my talents to their capacity. This process, endurance race, has provided a venue for me to get to know my grandparents, Dr. Jesse James and Barbara James, more than if I would have stayed in Texas, and it has allowed me to admire my grandfather for his intellectual talent, as a PhD in Electrical Engineering, a man educated at Auburn, Rice, and Georgia Tech, for his flexibility in helping others, even prisoners, that you will rarely find in a human being. I give thanks to my grandmother and Mom who have great talent in the kitchen and who make wonderful and nutritious meals for family and guest multiple times a day with joy. My father, the ultimate financial supporter of this project, is a man who believes in higher education and continues to learn in many different fields himself, as a dentist, pilot, financial manager, and, yes, hunter.

Table of Contents

List of Tables

Chapter 1

Scale Economies and Input Price Elasticities in Rated MFIs

Natalie James[2]

This is the first study to focus exclusively on estimating economies of scale and input price elasticities on microfinance institutions. Zacharias (2008) also explores this topic but uses a simple linear analysis of covariance model (ANCOVA), not the more appropriate system of simultaneous equations consisting of a translog cost function and cost share equations, which are used in this paper, and focuses only on scale. There have been other efficiency studies, including Gutierrez-Nieto (2005), Hermes et. al (2008), Mersland and Strom (2009), Caudill, Gropper, and Hartarska (2009), and Cull et. al (2007) etc., that use other techniques (data envelopment analysis, stochastic frontier analysis, and a mixture model approach). The results here confirm that MFIs can realize sizable cost advantages by expanding, can achieve lower cost with substitution of financial capital and labor for physical capital, and suggest opportunities for increasing returns to investors.

The data spans from 1997 to 2007 and includes 60 countries. This study is unique in that it provides empirical evidence of growth potential in the microfinance industry in terms of loan volume whereas much of the previous work in the field has been theoretical. Microfinance has

[2] The authors are grateful for the participants at the First European Research Conference in Microfinance at the Université Libre de Bruxelles (ULB) coordinated by Marek Hudon, particularly Beatriz Armendariz de Aghion (Harvard University), Ahmad Nawaz (my discussant, Phd student at the University of Göttingen in Germany), Cal Turvey (Cornell University), Marc Labie (CERMi – Center for European Research in Microfinance), and all other participants. Recognition is addressed to all sponsors of the First Microfinance Convention in California at Stanford University as well.

become increasingly popular as demonstrated by the focus of "creative capitalism or philanthro-capitalism" as framed by Bill Gates at last year's World Economic Forum (The Wall Street Journal, January 2, 2009) and the recent domestic and international conferences in California (at Stanford University) and Brussels (at the ULB) which brought together leaders in both academia and large entrepreneurial speakers from such organizations like Wells Fargo, Citigroup, and Chevron. Microfinance could be a potentially powerful tool to alleviate both domestic and international unemployment as well as an instrument to empower individuals who may be excluded from traditional banking. The intricacies of the industry may differ in the U.S. from abroad but the missions of the two are the same: to help individuals who have entrepreneurial spirits and can be productive individuals in their communities but who lack capital to undertake productive activities.

The results of this study show scale economies for this sample of 650 rated MFIs from around the world. The hypothesis is that economies of scale would be found as this sample of MFIs is small and there is potential to reach more clients and achieve constant returns to scale. A translog cost model is used to approximate the true cost function of this sample of firms. One output and two output models are specified with one output models in terms of Y1 (number of borrowers) or Loanport (volume of loans) and two outputs models in terms of (Y1 (number of borrowers) & Y2 (number of savers)) and (Loanport (volume of loans) & Volunsav (volume of savings)). The scale economy estimate of (0.65) for the one output model in terms of Y1 (number of borrowers) is comparable to Paxton's (2007) estimate of 0.64 for a sample of Mexican PSCI (Popular Savings and Credit Institutions) using SFA (Stochastic Frontier Analysis). In this sample, the scale value for the Mexican MFIs is 0.62). A much higher

economy of scale estimate is found (0.75) with the two output specification in terms of (Loanport (volume of loans) and Volunsav (volume of savings).[3]

The sample of MFIs was split by asset size into two groups: small and large MFIs. The scale economy estimates indicate that the large MFIs are moving towards their MES (minimum efficient scale). The Allen own, cross price, and implied own price elasticities show that physical capital is extremely price elastic for small and large MFIs in all output specifications. Labor and physical capital are substitutes, physical capital and financial capital are complements, and the relationship between labor and financial capital is inconclusive. Large MFIs have a stronger complementary relationship between financial capital and physical capital than small MFIs.

The rest of this essay is organized as follows: Section 1 discusses the recent proliferating literature on microfinance studies. Section 2 presents the translog cost model. Section 3 provides a brief discussion of the data. Section 4 discusses the empirical results, specifically, the parameter estimates, scale economy estimates, and Allen elasticities. Finally Section 5 summarizes the essay.

Section 1. A Selection of Microfinance Efficiency and Related Studies

While a multitude of papers have been written on scale economies of commercial banks, there are relatively few microfinance efficiency studies. Microfinance papers on various aspects of efficiency are those by Cull et. al (2007) whose main finding is important in that smaller loans are not associated with less profit, Gutierrez-Nieto et. al (2005) who use DEA (data envelopment analysis) and models based on various input and output sets, Hermes et. al (2008) who finds a

[3] Economies of Scale vary by the choice of outlier omission. This study excludes observations from the top 1% of observations for TC (total cost), P_L (the price of labor), P_F (the price of financial capital), P_K (the price of physical capital), y1 (number of borrowers), y2 (number of savers), loanport (volume of loans), and volunsav (volume of savings).

tradeoff between outreach and efficiency by using stochastic frontier analysis as shown by correlations between inefficiency and low ALBs (Average Loan Balances), Caudill, Gropper, and Hartarska (2009) who use a two stage mixture model approach to show that over time NGOs and Central Asian MFIs are not cost reducing over time, and Hartarska and Mersland (2009) who seek to explain efficiency through governance mechanisms. In addition, Mersland (2008) compares cost of ownership by Hansmann's (1996) Economic Theory of Ownership technique between SHFs (shareholder firms) and non-profit organizations and Cooperatives, Vanroose (2008) who seeks to explain microfinance development with macroeconomic variables, and Mersland and Strom (2008) who compare NGOs and SHFs (shareholder firms) under Schreiner's (2002) five components of efficiency. Zacharias (2008), is the only scale economy study, with an objective similar to the present paper but a simple ANCOVA model is used, not the classical simultaneous equations technique.

Within the efficiency studies, Gutierrez-Nieto et. al (2005) use DEA (data envelopment analysis) to score models based on different input and output sets. Two inputs (number of credit officers and operating expenses) and three outputs (interest and fee income, gross loan portfolio, and number of loans outstanding) were combined in 21 different specifications, and then rated according to efficiency. Four principal components of efficiency were highlighted including: 1) how efficient is the MFI under all input/output specifications, 2) is it an NGO, 3) is it efficient in terms of credit officers or with operating expense, 4) does it include or exclude gross loan portfolio as an output. While the 21 specifications shed light on DEA scoring, the interpretation of all combinations is somewhat cumbersome. Instead, the present study seeks to compare MFIs by the same inputs and outputs to better evaluate efficiency.

Hermes et. al (2008) finds a strong tradeoff between outreach and efficiency using stochastic frontier analysis (SFA) on 435 MFIs for data between 1997-2007. A translog cost frontier and inefficiency equation were estimated simultaneously by using maximum likelihood. The results displayed a direct correlation between inefficiency and lower average loan balances, and inefficiency and percent of woman served. Younger MFIs were found to be more efficient than older MFIs and African MFIs. The conclusion was that commercialization may induce efficiency and investors are looking for optimal risk/return tradeoffs or diversification and not maximum efficiency of MFIs.

Caudill, Gropper, and Hartarska (2009) use a two stage cost mixture approach for Eastern Europe and Central Asian data for 2003 and 2004. The first stage uses a technique which segments the sample into cost efficient MFIs from less efficient MFIs with controls for age to capture possible learning by doing. The second stage auxiliary equations use control variables to explain the probability that an MFI belongs to the regime of MFIs who improve their efficiency in time and those that do not. Factors that affect this probability include MFI type, size, loans overdue more than 30 days, and a percentage of the write-off ratio. Macroeconomic variables were not found to be significant. The authors mention that they would have liked to have conducted a scale economy study but simply lacked the data to do so.

Hartarska and Mersland (2009) conduct an efficiency study on governance mechanisms. They first estimate a stochastic cost frontier which accounts for the sustainability mission (cost minimization) of MFIs and within the cost function measure outputs as the number of active clients to capture the outreach mission of the MFIs. Estimated technical efficiency coefficients are then regressed on various measurable governance variables. Their policy recommendations

are that the CEO and board chair position should be separated, that debt holders and clients enhanced board efficiency while employees did not.

While the efficiency papers in the microfinance literature use somewhat typical efficiency analysis, they do not focus on scale economies or elasticities of substitution between factors of production. This current study adds to the literature by focusing on estimating elasticities of substitution and scale economies in a sample of rated MFIs.

Some non efficiency studies are also relevant. For instance, Mersland (2008), compares the cost of ownership by different organizational types and finds little evidence to suggest that SHFs operate more efficiently than COOPs and NPOs. This result provides confidence in pooling different organizational types to estimate cost efficiency and elasticities. This is what has been done in the current study.

Mersland and Strom (2008), compare NGOs and SHFs (shareholder firms, specialized microfinance institutions) according to 5 aspects of outreach proposed by Schreiner (2002) which include cost, depth, breadth, length, and scope. The proposed hypothesis is that NGOs reach poorer clients at the expense of cost efficiency, breadth, length (long-run viability proxied by ROA), and scope while SHFs are less socially beneficial (meaning that their clients are less poor) but operate more efficiently, reach more clients, are more likely to survive in the long run, and offer more products because of more lenient regulations on the deposit side and with more deposits, more loan options can be secured. The results show that NGOs and SHFs were not found to differ much as initially expected. SHFs were not found to be more cost effective than NGOs; in fact, the ROA was higher for NGOs than for SHFs, meaning that NGOs have a business plan to sustain them in the long run. This is a similar result found in essay number two.

Cull, Demirguc-Kunt, and Morduch (2007) investigate the relationship between the rate of interest charged by the lender and profit. Lenders providing individual loans are found to increase their profits by charging higher interest rates more so than lenders using village banks or solidarity lending products, but only until a certain point when decreases in demand and adverse selection set in. Cull et. al (2007) finds that institutions that make smaller loans are not necessarily less profitable which means that depth of outreach and profitability can be achieved. However, larger loan size was associated with lower average cost for individual and group-based lenders but only up to a point. Profit was found to be associated with outreach over size, which might have meant that some MFIs were not operating at their MES (minimum efficient scale).

Zacharias (2008), focuses exclusively on scale economies of MFIs yet uses a simple linear analysis of covariance model (ANCOVA). He begins with a graphical display of the inverse relationship between the MFI's sample of average cost to the gross loan portfolio which shows, even before doing any empirical work, that larger MFIs have a cost advantage. He finds that a 1% growth in gross loan portfolio is correlated with a 0.0626% reduction in average cost.

He splits the sample by NGO and Non-NGO according to annual and regional efficiency and finds NGOs to be more efficient than Non-NGOs. However, a prior U.S. commercial banking study by Hunter and Timme (1986) found that economies of scale computed without interest can be misleading. The current study is a step above Zacharias' (2008) research in that it employs a more advanced empirical method of a simultaneous system of equations, the preferred technique of commercial banking experts.

Section 2. The Estimation Approach

The production process can be depicted by a general production function of the form

$$Y = f(L, K, F) \quad (1)$$

Where Y can denote a single or double output (number of borrowers, used exclusively or with number of savers) and volume of loans (used exclusively or with volume of savings)) and L, K, and F denote labor, physical capital, and financial capital, respectively.

The two main approaches of cost function estimation are discussed in detail in Das and Das (2007). They are the intermediation and production approaches. What distinctly separates the two methods is the inclusion of interest expense on deposits in the intermediation approach while the production approach focuses only on the operating expense. The intermediate approach usually uses the value of loan portfolio in dollars as the output, deposits as an input, and considers the interest paid on deposits a legitimate expense (Tadesse, 2006). The output for the production method is number of transactions or in our case, number of borrowers (Das and Das, 2007).

This study's approach follows Caudill et. al (2009) and Hermes et. al (2008) and uses a combination of the intermediation and production approaches (or a quasi-intermediation approach). In particular, interest paid on deposits is accounted for with the cost of financial capital (the intermediation approach), but the output is measured by the number of borrowers (and savers), as in the production approach. While a cost function with output measured by the volume of loans and deposits is also estimated here, the outreach objective of MFIs to serve marginal clientele is better captured when outputs are measured by the number of clients (borrowers and savers).

The cost function has been the dominant approach in efficiency studies while the profit function may have some advantages in that output and input inefficiencies can be measured. The cost function assumes exogenous output and uses input prices while the profit function uses input

and output prices, which is problematic for a study of MFIs because loan price data is not collected. The profit function is suitable for price taking behavior in input and output markets while the cost function is suitable for price taking behavior in the input market and some market power in the output market (Varian, 1984). Thus, the cost function is more appropriate since MFIs usually have market power in offering loans and savings products but have to pay market prices for inputs such as physical assets, financial capital and salaries for (relatively) skilled labor (Ellinger, 1997)

We estimate the translog cost function similar to the one used in Karafolas, S. and Mantakas, G. (1996), Bernstein (1996), and Gropper (1991):

$$\ln(C) = \alpha_0 + \sum_1^2 \alpha_1 \ln(p_1) + \sum_1^2 \beta_1 \ln(y_1) + \frac{1}{2}\sum_1^2 \gamma_{11} \ln(p_1)\ln(p_1) + \frac{1}{2}\sum_1^2 \delta_{11} \ln(y_1)\ln(y_1) + \kappa_{12} \ln(p_1)\ln(p_2) + \sum_1^2\sum_1^2 \rho_{11} \ln(p_1)\ln(y_1) + \ln u \quad (2)$$

where C is total cost scaled by the price of physical capital[4], p_1 is the price of labor scaled by the price of physical capital (p_3), p_2 is the price of financial capital scaled by physical capital (p_3), y_1 is the number of borrowers or the volume of loans, y_2 is the number of savers or the volume of savings; $\alpha, \beta, \gamma, \delta, \kappa, and\ \rho$ are parameters to be estimated, and ln u is normally distributed.

The translog cost model is not the only model used to find scale economies. Some studies, (Das and Das, 2007), have used the fourier flexible functional form which is basically the translog cost model with *sin* and *cosin* terms added to it. The translog form is used instead of the traditional Cobb-Douglas or CES functional form to estimate u-shaped average cost functions (Tadesse, 2006).

We estimate four specifications: one with a single output measured by the number of active borrowers (y1), one with two outputs, number of borrowers (y1) and number of savers (y2), and as two robustness checks, models with output(s) measured by the dollar value, namely a model with one output measured by the value of loan portfolio (loanport) and one specification with volume of loans and volume of savings.[5]

The translog cost model (whether a single output or double output model) is estimated simultaneously with cost share equations derived from Shepherd's Lemma, as typical in the literature on economies of scale. Prior to the estimation, symmetry constraints (accounted for across the two share equations on labor and finance) and the linear homogeneity of the cost function constraints were imposed. With respect to input prices this implies:

$$\alpha_1 + \alpha_2 = 1, \gamma_{11} + \kappa_{12} = 0,\ \gamma_{22} + \kappa_{12} = 0,\ \rho_{11} + \rho_{21} = 0,\ \rho_{12} + \rho_{22} = 0 \qquad (3)$$

A symmetry condition is imposed across the labor and finance share equations. This constriction, along with the linear homogeneity constraints, is imposed *apriori,* as done by Gropper (1991), Bernstein (1996), and Karafolas, S. and Mantakas, G. (1996). Homogeneity in input prices is imposed by dividing all input prices and total cost by the price of capital (p_3).

We use the seemingly unrelated regression to estimate the translog cost function with labor and finance cost share equations (n – 1 cost share equations are needed) although a different combination of cost shares would produce similar results. The cost share equations are

[5] Technology could be included in the translog cost specification by adding a time element independently and interacting it with output and input prices. A technological advancement would mean that the average total cost curve of the MFI would fall over time suggesting an inverse relationship between time and cost.

derived from Shepherd's lemma, $\partial \ln C / \partial \ln p_i$, with the restrictions of symmetry and linear homogeneity applied as described above.

For instance (from equation 2),

$$S_1 = dlnC/dlnP_1 = \alpha_1 + \gamma_{11} ln\,(p_1) + \kappa_{12}\ ln\,(p_2) + \rho_{11} ln\,(y_1) + u \qquad (4)$$

where S_1 is the labor input share of the total cost. The translog cost function is estimated with the labor share equation and the financial capital share equation to obtain more efficient estimates.

Using equation (2), a partial scale economy can be found by taking the derivative of lnC w.r.t. the natural log of the number of borrowers:

$$SE = dlnC/dlnY1 = B_1 + \delta_{11} \ln(y_1) + \rho_{11} \ln(p_1) + u \qquad (5)$$

However, since all variables are mean scaled, the partial scale is the coefficient of number of borrowers in the model with number of borrowers and number of savers, and the overall scale economy is the sum of the partials. The overall scale economy for a one output model is the coefficient of number of borrowers or volume of loans.

When SE equals one, it indicates constant returns to scale, when SE <1 there are increasing returns to scale or economies of scale, and when SE >1 there are decreasing returns to scale or diseconomies of scale. Economies of scale are said to exist if an increase in output, holding all input prices constant, causes a less than proportional increase in total cost. If this result is found, MFIs would benefit from either expanding output (number of clients or volume of services) or consolidating to take advantage of cost-saving opportunities. Since, compared to larger datasets such as those by the MIXmarket, this sample is one of small MFIs, economies of

scale are likely to exist and would suggest benefits if MFIs were to move rightward along their cost curve.

In addition to offering the first estimates of scale economies for the industry, this study also calculates (Allen) own and cross price elasticities of substitution for the production inputs used in the model (labor, physical capital, and financial capital) to show how MFIs use inputs to achieve their objectives.

Elasticity Estimates

Using the parameter estimates from the translog cost function, the Allen-Uzawa elasticities of substitution are:

$$\sigma_{12} = 1 + (\kappa_{12}/S_1S_2) \text{ for } 1 \neq 2; \qquad \sigma_{11} = (\gamma_{11} + S_1^2 - S_1) / S_1^2 \tag{6}$$

where κ_{12} = the respective cross-price coefficient (from eq. (2))

γ_{11} = the respective own-price coefficient (from eq. (2))

S_1 or S_2 = the respective input share = $[(P_1 * Q_1)/TC]$ (likewise for S_2)

The own and cross-price elasticities of substitution are defined as:

$$\varepsilon_{12} = (\kappa_{12} + S_1S_2)/S_1 = \sigma_{12}S_2 \text{ where } 1 \neq 2 \qquad \varepsilon_{11} = (\gamma_{11} + S_1^2 - S_1)/S_1 = \sigma_{11}S_1 \tag{7}$$

where the input shares, S_1, are at the sample means. The own price elasticity should be negative in accordance with the law of demand. Inelastic demand could indicate more vulnerability to monopsonistic power. Stiroh (1999) found that the own-price Allen elasticities of substitution were generally larger for the lowest cost thrifts.

Section 3. Brief Data Discussion

This data set includes data from rated microfinance institutions in 60 countries. The rating reports are made up by a third party (the rating agency) and are publically available at www.ratingfund.org. This data set was graciously provided by Roy Mersland in Norway who spent a year assembling the data. For each microfinance institution there are at least three annual observations. The mean year is 2003 while the earliest year is 1997 and the latest year reported is 2007, out of the 1,254 annual MFI observations. Appendix A shows a list of the countries and the number of observations per country in the sample. Table 1.1 provides a summary of statistics on all output and input variables used in the analysis.

Table 1.1

Summary Statistics for the Rated MFI Sample of 1,254 Annual Observations

Variable	Description	Observations	Mean	Standard Deviation	Minimum	Maximum
Inputs						
xlabor	Quantity of Labor	729	67	82	3	826
wlabor	Price of Labor	729	6494	3864	35	19,342
xphyscap	Quantity of Capital	729	224,384	344,714	245	2,458,176
wphyscap	Price of Capital	729	3	3	0.04	25
xfincap	Quantity of Financial Cap	728	2,658,776	3,811,546	597	1.84e+08
wfincap	Price of Financial Cap	650	0.07	0.06	0.0007	0.44
Outputs						
y1	Number of Borrowers	729	8,826	12,796	20	120,553
y2	Number of Savers	729	2,497	9,359	1	98,341
loanport	Volume of Loans	729	3,467,519	4,224,685	3586	2.97e+07
volunsav	Volume of Savings	729	460,418	2,166,383	10	2.7e+07

Section 4. Discussion of Empirical Results

This study uses the translog cost model used on numerous occasions in the commercial banking literature to compute scale economies on a sample of 1,254 MFIs from around the world. Scale economies are computed for 4 output specifications, including one and two output models. As

the goal of MFIs is to reach as many poor as possible, it is important to examine the scale with one output Y1, the number of borrowers, and with Y1 & Y2, the number of borrowers and the number of savers. The other 2 models include a one output specification with Loanport, volume of loans, and a two output specification with Loanport & Volunsav, or volume of loans and volume of savings.

Table 2 displays the 4 scale values which are Y1 (0.65), Y1 & Y2 (0.65), loanport (0.74), and loanport & volunsav (0.75) on 650 observations for March 30, 2009 data. The scale drivers are volume of loans over number of loans and volume of savings over number of savers. The scale values reflect that efficiency does not change much with participation in multiple activities (both lending and collecting savings). There does not appear to be scope in collecting deposits. The smaller scale values for outreach suggest inefficiency and scale may be reached with government subsidies only[6].[7]

Table 3 shows the scale values for the small and large MFIs in this sample in terms of y1- number of borrowers, and loanport - volume of loans. There is not much difference in the scale value found for small and large MFIs in the specification with y1 (number of borrowers) as the output, although a direct relationship does exist between size and efficiency for volume of loans (loanport). Large MFIs have a scale value of 0.55 in terms of outreach (y1) while small MFIs have a scale value of 0.50 (a 9.8% increase in efficiency with size), while the mean value of number of borrowers for the large MFIs is 13,588, approximately three times the mean value of number of borrowers for the small MFIs which is 4,077. However, when loan volume is used to represent the MFIs' output (the mean value of volume of loans for the small MFIs is 869,318

[6] Zero values for Y2, number of savers, were replaced with one. Zero Values for volume of savings were replaced by 10.

[7] However, scale values calculated with the inclusion of Y2 (number of savers) or volunsav (volume of savings) should be interpreted with caution as the number of observations that exceed zero on Y2 in this sample is 467 and the number of observations that exceed zero on volunsav (volume of savings) is 408.

compared to the mean value of volume of loans for the large MFIs which is 6,072,858), the scale value of the large MFIs increases by 24% (from 0.5468 to 0.6968), meaning loan volume drives the MFIs to MES (minimum efficient scale) over number of borrowers.

Table 4 lists the Allen own, cross price, and implied own price elasticities for Y1, Y1 & Y2, Loanport, and Loanport & Volunsav specifications for the entire sample. The most interesting finding shows that a greater complementary relationship exists between physical and financial capital for the specification measuring outputs in numbers of clients Y1 and Y1 & Y2 than for that measuring outputs in volume Loanport and Loanport & Volunsav, which suggest that outreach to new clients (entailing more risk and an increase in asymmetric information) is more expensive than giving a larger loan to a better qualified client, MFIs are sensitive to the increase in the cost of financial capital and try to reach new clients by reducing expenditures on physical capital.

The implied own price elasticities (own LL, own KK, and own FF) at the bottom of the 4 columns in **Table 4**, suggest that while holding the number of borrowers (y1) or loan volume (loanport) constant, labor and financial capital are necessities (the implied own price elasticity for financial capital is very low in terms of loan volume), while physical capital is elastic. Loan extension depends primarily on loan officers and financial capital (be it in terms of equity, debt, or most likely in this case, the interest rate offered by other banks).

Table 5 contains the Allen own, cross, and implied own price elasticities for the small and large MFIs in terms of y1 and loanport. Labor and physical capital are substitutes for both small and large MFIs (transactions can take place through loan officers or ATMs/mobile phones), physical capital and financial capital are complements (savings are funneled via technical infrastructures), while labor and financial capital are substitutes in terms of (y1) and

complements in terms of loan volume. The result could be reflective of the scale reached with loan volume and the lack of scale with outreach (y1). The larger loan volume may fund mobile phone technology enabling cost savings on labor. However, the Allen own price elasticity on financial capital in terms of outreach (y1), especially for the small MFIs, strongly exceeds the value in terms of loanport which suggest that lending to new clients is risky and when trying to pursue the outreach objective, small and large MFIs are especially sensitive to the price of financial capital.

Here, both the Allen own price and implied own price elasticities for labor show that labor is a necessity for the small and large MFIs and for (y1) outreach and (loanport) depth, while physical capital is not a necessity for lending. Financial capital is a necessity for loan volume but MFIs are sensitive to the price of financial capital in terms of outreach because outreach to new clients is costly.

All 4 models show that physical and financial capital are strongly complementary. Each Allen own price elasticity and each implied own price elasticity is negative in accordance with demand theory while physical capital is strongly elastic according to the Allen own price elasticity while only slightly elastic with the implied own price elasticity. The Allen own price on financial capital is elastic in terms of the 2 outreach specifications (y1) and (y1 and y2), but not in terms of the depth specifications (loanport) and (loanport & volunsav) and the own price elasticity on labor in terms of the outreach specifications is more price sensitive showing the risk in new client lending which depends on "character scoring" (a method of offering a loan to a client based on conversations the loan officer has with potential clients and on the loan officer's optimism of future client success).

Future research should focus on dynamic adjustments and longer term asset effects on the Allen own, cross price, and implied elasticities.[8] Other studies should focus on regional scale economies (the subject of the second essay, which uses MixMarket data), on lending methodology, firm organization, and on regional elasticities.[9] This study could be applied to other cost frontier methodologies to determine the actual cost frontier and highlight the firms that are producing far from the minimum cost frontier. An emphasis could be placed on scale and scope economies to determine lowest cost MFIs.

A look at a comparison of elasticities between Peru and Brazil in this sample shows that Peru has higher elasticities in some respects which might stress that Peruvian MFIs are cost minimizing to a greater extent than Brazilian MFIs in this sample due to a more competitive environment[10].[11] Additionally, with more detailed data, one could combine cost efficiency with interest rates extended to particular clients and include external factors such as number of woman borrowers, a percentage of the loan losses, and a dummy variable to break more competitive environments from less competitive environments over time.[12]

As all economies of scale values were found to be less than one, the expected hypothesis is confirmed. This selected sample of MFIs is small and previous literature has suggested that most MFIs are operating inefficiently, meaning that they have outreach potential. For example, the Federation in Tianjin, China reached less than 2,000 clients after more than seven years when it should have reached 30,000 clients according to an analyst[13]. This result suggest that the goal of these MFIs should be to lend to more borrowers to capture the economies of scale that exist to

[8] I am grateful to Calum Turvey for this suggestion.
[9] I thank my discussant, Ahmad Nawaz, for his comments on my paper and expertise in Microfinance.
[10] Mark Labie was a great participant at the First European Conference in Brussels, Belgium.
[11] Regional elasticities available from the authors.
[12] A suggestion by Beatrice Armendariz of Harvard University.
[13] "Microfinance in China: Growth and Struggle", Knowledge @ Wharton

achieve a minimum efficient scale (MES) so that donors' and investors' funds would be used to their fullest potential and more disadvantaged clients could be served.

The implied own price elasticities are smaller than the Allen own price elasticities, and have more relevance, as pointed out by Stiroh (1999). They validate the Allen elasticities as physical capital is elastic while labor and financial capital are inelastic. Thus, MFIs can continue to lower cost as they have been doing with less capital structures to a certain extent (as physical capital was found to be elastic but complementary with financial capital) and more ATMs, point of sale systems, mobile phones, and partnerships with local post offices and banks should be utilized. For example, the Hatton National Bank in Sri Lanka formed a partnership with the post offices to make it easier to reach potential clients in rural areas (Knowledge @ Wharton).

The values for the scale economies being less than one indicates that profit maximization has not yet been achieved and that the industry (reflected with this sample of MFIs) has growth potential. Individual investors and firms should take note of this industry because the lending methodology at the crux of microfinance has lead to high repayment rates (as high as 98%) and the individuals that make up the clientele have shown potential to be entrepreneurial savvy (e.g. some have created export markets at Pro Mujer), but have just not had the advantages of many in developed nations.

Section 5. Conclusion

The goal of scale efficiency analysis is to inform the major decision makers on how to best use donor funds, by minimizing cost and improving returns to MFIs whose objective is to meet the financial needs of clients with an entrepreneurial spirit but simply lack capital. Since outreach is

the most important mission of the MFIs, the mission is best met by ensuring highest cost savings by achieving scale efficiency.

MFIs provide opportunities to people who are entrepreneurial minded but fail to get the funds they need from traditional banks because they are considered risky. The opportunities provided by these institutions are powerful. There have been exceptional case studies from the microfinance service, including an example of women clients at ProMujer in Peru who developed such a marketable product with a well-developed business plan that an export market exploded. One client even reported that the opportunity provided by these institutions gave her a will to live.

This study examines the growth opportunities of a sample of MFIs. Results indicate substantial cost savings from achieving optimal scale for the average MFI in the sample. Calculated elasticities of substitution suggest that MFIs can lower cost with the correct complementary use of physical and financial capital, with more attention paid to financial capital, and that small MFIs are possibly utilizing their funds to the best of their ability at their current scale. Given that rural finance is becoming the new frontier in microfinance, these findings show how MFIs can economize by the appropriate use of inputs. Similar studies and calculation of elasticities by organizational type, region of operation, MFI size and rural/urban markets served will be even more informative and should be carried out as more data becomes available.

Table 1.2
Rated Data
Scale Economies on 4 Output Specifications (Y1, Y1 & Y2, Loanport, Loanport & Volunsav)

Cost	One Output (Y1)	Two Ouputs (Y1 and Y2)		One Output (Loanport)	Two Outputs (Loanport & Volunsav)
	Coefficient	Coefficient		Coefficient	Coefficient
Pl	0.7542***	0.8051***	Pl	0.4706***	0.3974***
Pf	0.2458***	0.1949***	Pf	0.5294***	0.6026***
PlPl	0.0276**	0.0306**	PlPl	0.1500***	0.1479***
PfPf	0.0276**	0.0306**	PfPf	0.1500***	0.1479***
PlPf	-0.0276**	-0.0306**	PlPf	-0.1500***	-0.1479***
Y1	**0.6540*** **	**0.5465*** **	Loanport	**0.7359*** **	**0.7933*** **
Y2		**0.1039** **	LoanLoan	0.0652***	0.0655***
Y1Y1	0.0690***	0.0664***	Volunsav		**-0.0392**
Y2Y2		0.0237	VolVol		-0.0085
Y1Y2		-0.0262*	LoanVol		0.0106
Y1Pl	0.0198*	0.0205*	LoanPl	-0.0537***	-0.0553***
Y1Pf	-0.0198*	-0.0205*	LoanPf	0.0537***	0.0553***
Y2Pl		0.0057	VolPl		-0.0084*
Y2Pf		-0.0057	VolPf		0.0084*
Constant	0.1137***	0.1614	Constant	0.0075	0.0666
Labor Share					
Pl	0.1832***	0.1690***	Pl	0.2221***	0.2081***
Pf	-0.1807***	-0.1674***	Pf	-0.1939***	-0.1761***
Y1	0.0553***	0.0629***	Loanport	-0.0765***	-0.0651***
Y2		-0.0293***	Volunsav		-0.0250***
Constant	-0.0342**	-0.2208***	Constant	-0.0977***	-0.3168***
Finance Share					
Pl	-0.1807***	-0.1674***	Pl	-0.1939***	-0.1761***
Pf	0.6300***	0.6151***	Pf	0.5453***	0.5269***
Y1	-0.0814***	-0.0921***	Loanport	0.1123***	0.0945***
Y2		0.0408***	Volunsav		0.0377***
Constant	-0.0320	0.2252***	Constant	0.0172	0.3509***
N	**650**	**650**		**650**	**650**
Cost r-square	**0.8783**	**0.8825**		**0.8923**	**0.8944**
Labor r-square	**0.3212**	**0.3732**		**0.3346**	**0.3966**
Finance r-square	**0.5253**	**0.5350**		**0.5280**	**0.5371**
Economies of Scale	**0.6540**	**0.6504**		**0.7359**	**0.7541**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost2]Pl2 + [Cost2]Pf2 = 1, (b) [Cost2]PlPl + [Cost2]PlPf= 0, (c) [Cost2]PfPf + [Cost2]PlPf = 0, (d) [Cost2]Y1Pl + [Cost2]Y1Pf= 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings) (for 2 outputs, such as Y1 and Y2 – there is an additional constraint)

(e) [LaborShare2]Pf2 - [FinanceShare2]Pl2 = 0. The top 1% of outliers on tc, y1, y2, loanport, volunsav, wlabor, wphyscap, and wfincap were voided to prevent a bias of extremely large MFIs in the sample. Y2 (number of savers) was given a 1 if the value was zero and Volunsav (Volume of savings) was given a 10 if the value equaled zero.

Table 1.3
Rated Data
Scale Comparison Between Small and Large MFIs in the Sample[14]

Cost	Small MFI (1-365) (Y1)	Large MFI (366 - 729) (Y1)	Cost	Small MFI (1-365) (Loanport)	Large MFI (366 - 729) (Loanport)
	Coefficient	Coefficient		Coefficient	Coefficient
Pl	0.6524***	0.7213***	Pl	0.5002***	0.4703***
Pf	0.3476***	0.2787***	Pf	0.4998***	0.5297***
PlPl	0.0696***	0.0704***	PlPl	0.1475***	0.1496***
PfPf	0.0696***	0.0704***	PfPf	0.1475***	0.1496***
PlPf	-0.0696***	-0.0704***	PlPf	-0.1475***	-0.1496***
Y1	**0.5009*** **	**0.5525*** **	Loanport	**0.5468*** **	**0.6968*** **
Y1Y1	0.0716**	0.1262***	LoanLoan	-0.0643	0.2500**
Y1Pl	0.0269*	0.0511**	LoanPl	-0.0682**	-0.0886**
Y1Pf	-0.0269*	-0.0511**	LoanPf	0.0682**	0.0886**
Constant	0.1747***	0.1490***	Constant	0.0018	-0.0159
Labor Share					
Pl	0.2484***	0.2172***	Pl	0.2377***	0.2158***
Pf	-0.2432***	-0.1820***	Pf	-0.2247***	-0.1641***
Y1	0.1316***	0.0890***	Loanport	-0.0420	-0.1124***
Constant	0.0149	-0.0092	Constant	-0.0697**	-0.0712***
Finance Share					
Pl	-0.2432***	-0.1820***	Pl	-0.2247***	-0.1641***
Pf	0.5905***	0.6573***	Pf	0.5177***	0.5767***
Y1	-0.1704***	-0.1091***	Loanport	0.0376	0.2638***
Constant	-0.1009*	0.0940**	Constant	-0.0430	-0.0133
N	**315**	**335**		**315**	**335**
Cost r-square	**0.8384**	**0.8375**		**0.7947**	**0.7905**
Labor r-square	**0.4453**	**0.3437**		**0.3436**	**0.3109**
Finance r-square	**0.5465**	**0.5637**		**0.5007**	**0.5688**
Economies of Scale	**0.5009**	**0.5525**		**0.5468**	**0.6968**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost2]Pl2 + [Cost2]Pf2 = 1, (b) [Cost2]PlPl + [Cost2]PlPf = 0, (c) [Cost2]PfPf + [Cost2]PlPf = 0, (d) [Cost2]Y1Pl + [Cost2]Y1Pf = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings) (for 2 outputs, such as Y1 and Y2 – there is an additional constraint)

(e) [LaborShare2]Pf2 - [FinanceShare2]Pl2 = 0. The top 1% of outliers on tc, y1, y2, loanport, volunsav, wlabor, wphyscap, and wfincap were voided to prevent a bias of extremely large MFIs in the sample. Perhaps only the top 1% of outliers on TC, number of borrowers (y1), and loan volume (loanport) should be deleted since the prices of the inputs are also embedded in TC. As number of savers (y2) is replaced with a 1 when 0 and volunsav (volume of savings) is replaced with a 10 when 0, the scales with the inclusion of number of savers and volume of savings are strange for the small MFIs. The scale on (Y1 and Y2) for the Small MFIs is 0.4772 and for (Loanport and Volunsav) 0.1267. For the large MFIs, the scales with the inclusion of number of savers and volume of loans make more sense – for (Y1 and Y2) (0.5529) and for (Loanport and Volunsav) (0.6519). Perhaps the small MFIs in this sample do not collect much of a savings volume or deposits whereas the volume of savings for the large MFIs in the sample help the large MFIs to achieve (MES).

[14] The scale value depends significantly on the omission of outliers on certain variables. If outliers are taken out on just total cost (the top 1%) or on total cost, y1 (number of borrowers), y2 (number of savers), loanport (volume of loans), volunsav (volume of savings), P_L (the price of labor), P_K (the price of physical capital), and P_F (the price of financial capital) and not on the Q_L (the quantity of labor), Q_K (the quantity of physical capital), and Q_F (the quantity of financial capital), then there are 315 observations for the small MFIs in the sample, the scale on Y1 and Y2 (0.5981), and the scale on Loanport & Volunsav (0.2765), which is a drastic difference from the results above and would suggest that small MFIs have greater outreach and perhaps less emphasis on reaching the less poor. For the larger MFIs, the scale on Y1 and Y2 (0.5417) and the scale on Loanport & Volunsav (0.603) suggest a balance between the two missions: outreach and depth with 335 observations. Results also vary if Y2 (number of savers) = 0 is replaced with a 1 and Volunsav (Volume of Savings) = 0 is replaced with a 10.

Table 1.4

Allen Own, Cross Price, and Implied Own Price Elasticities for 4 Output Specifications

Labor Share = 0.4454 Finance Share = 0.2090 Capital Share = 0.3444

Y1	Y1 and Y2	Loanport	Loanport & Volunsav
Allen LK = 0.9835	Allen LK = 0.9895	Allen LK = 0.8163	Allen LK = 0.7917
Allen LF = 0.7038	Allen LF = 0.6707	Allen LF = -0.6111	Allen LF = -0.5887
Allen KF = -5.2428	Allen KF = -5.2218	Allen KF = -3.8825	Allen KF = -3.8747
Allen LL = -1.1064	Allen LL = -1.0908	Allen LL = -0.4894	Allen LL = -0.4999
Allen KK = -7.0845	Allen KK = -6.5106	Allen KK = -7.8147	Allen KK = -6.8210
Allen FF = -3.1539	Allen FF = -3.0834	Allen FF = -0.3517	Allen FF = -0.3993
Own LL = -0.4927	Own LL = -0.4858	Own LL = -0.2179	Own LL = -0.2226
Own KK = -2.4397	Own KK = -2.2420	Own KK = -2.6911	Own KK = -2.3489
Own FF = -0.6591	Own FF = -0.6444	Own FF = -0.0735	Own FF = -0.0834

$B_k = 1 - B_L - B_F$,LK = -LL – LF, FK = -FL – FF, and KK = $-B_K$ – LK – FK (needed to compute above elasticities as coefficients with capital were not available).

Table 1.5

Allen Own, Cross Price, and Implied Own Price Elasticities for Small and Large MFIs in the Sample

Small MFI Labor Share = 0.4600
Small MFI Finance Share = 0.1815
Small MFI Capital Share = 0.3584

Large MFI Labor Share = 0.4307
Large MFI Finance Share = 0.2364
Large MFI Capital Share = 0.3303

Small MFI (Y1)	Large MFI (Y1)	Small MFI (Loanport)	Large MFI (Loanport)
Allen LK = 0.9683	Allen LK = 0.7530	Allen LK = 0.9207	Allen LK = 0.6367
Allen LF = 0.1665	Allen LF = 0.3085	Allen LF = -0.7663	Allen LF = -0.4696
Allen KF = -4.3384	Allen KF = -5.0857	Allen KF = -3.5035	Allen KF = -4.2826
Allen LL = -0.8450	Allen LL = -0.9422	Allen LL = -0.4769	Allen LL = -0.5151
Allen KK = -7.5020	Allen KK = -7.4593	Allen KK = -8.0715	Allen KK = -7.7110
Allen FF = -2.3965	Allen FF = -1.9700	Allen FF = -0.0330	Allen FF = -0.5524
Own LL = -0.3887	Own LL = -0.4058	Own LL = -0.2194	Own LL = -0.2218
Own KK = -2.6884	Own KK = -2.4641	Own KK = -2.8925	Own KK = -2.5472
Own FF = -0.4351	Own FF = -0.4658	Own FF = -0.0060	Own FF = -0.1306

$B_k = 1 - B_L - B_F$,LK = -LL – LF, FK = -FL – FF, and KK = $-B_K$ – LK – FK (needed to compute above elasticities as coefficients with capital were not available).

Chapter 2

MFI Efficiency by Organizational Type and Region

The focus of this essay is on estimating economies of scale for various subgroups of MFIs using a larger and more comprehensive dataset assembled from data publicly available at the MixMarket Exchange, and last accessed in November 2008. Unlike the dataset of rated MFIs used in the first essay, the dataset for this essay has only two derived input prices, one the ratio of operating expense per worker and one of financial expense to total liability as in Hermes et al 2008, however, it contains more MFIs and their annual observations. Scale results were found with regard to outreach and depth specifications, with respect to size, institutional type, region, and with the inclusion of the percentage of woman, the write-off ratio, and loans extended to the bottom half of the poverty line. The results reveal that non-profits or NGOs are the most numerous of all of the financial intermediaries analyzed, the financial intermediaries include NGOs as well as rural banks, non-bank financial institutions, and Coops. The NGOs were found to reach the poor most effectively in developing countries. The regional scale determinations show that the Eastern European and Central Asian microfinance institutions operate with precise efficiency when output is measured with loan volume while the African microfinance institutions stand to gain the most from external funds. While other studies, such as Cull et. al (2007) find that women increase production cost, this study finds that lending to women promotes scale.

Microfinance institutions have a double bottom line: to be solvent and to promote outreach. Consistent with Hartarska and Nadolnyak (2007) who conclude that regulation does

not improve financial results, the same is true with the current findings. As the NGOs in this study operate at the highest degree of scale, they are more equipped to serve the poorest of the poor at the least cost. Cooperatives follow in terms of efficiency succeeded by the Non-Bank Financial Institution and the Rural Banks. This conclusion is interesting as NGOs, Coops, and Non-bank financial institutions are not regulated by a banking authority while Rural banks are supervised by a banking authority. However, Coops offer savings and time deposits but their cost are more contained by offering loans to members only who control for monitoring and enforcement. Future studies should address the reliance of government and donor funds in each developed country so that the microfinance industry can be sustainable when funding is discontinued (Nawaz, 2009).

Section 1: A Brief Discussion of Recent Efficiency Studies

As studies have found scales with samples of MFIs using SFA (stochastic frontier analysis), Paxton (2007), DEA analysis, Nawaz (2009) and Gutierrez-Nieto et al. (2007), this study seeks to find scalability with the SUR technique with a translog cost model and two input share equations, which has been used in commercial banking studies, such as Karafolas & Mantakas (1996), Bernstein (1996), Gropper (1991), Tadesse (2006), Das and Das (2007)[15], Harimaya (2008), and Altunbas and Molyneux (1996).

Earlier microfinance studies were less empirically focused because of lack of data[16] and much of the literature tried to address whether the poorest of the poor were being reached. The literature has focused on women empowerment, impact assessments, and rural outreach. Only in

[15] Das and Das (2007) actually use the fourier flexible functional form which is an expanded version of the translog cost model with added sine and cosine terms.
[16] The Microfinance Banking Bulletin was first published in 1997. www.themix.org/microbanking-bulletin/microbanking-bulletin

the last decade or so has it evolved to meet the same standards found in the commercial banking literature. Efficiency studies can now be found which apply DEA, SFA, benchmarking techniques, and governance mechanisms that directly impact financial performance ratios.

Brau and Woller (2004) review over 350 articles and claim that the microfinance literature has yet to break into the mainstream finance literature. This era has ended with high quality empirical work accepted into the Journal of Banking and Finance, Mersland and Strom (2009), who conclude that MFI type, whether non-profit or a shareholder firm does not affect outreach or financial performance. This conclusion has powerful policy implications, perhaps suggesting that non-profits should also be allowed to move deposits around like the shareholder organizations. However, the non-profit organizations have less appealing board structures compared with those of the shareholder financial institutions that have smaller boards, internal auditors, and a regulator (Mersland and Strom, 2009).[17]

Microfinance looks to be moving in a similar direction that banks have taken as practitioners see almost more value in offering sustainable savings services[18] and future research will focus on micro-insurance, which at the present is not popular because the poor would like to use microfinance for emergency financial needs. Nonetheless, all governments should place their attention on the less fortunate especially in times of extraneous macroeconomic depressions such as the one in the U.S., the most severe crisis since 1933, which impacts the developing world, similar to that of the Asian crisis (see Dwyer and Tkac, 2009 for the effects of the run on the prime money market funds on the commercial paper market, Kim and Koo (1999) for the Asian Financial Crisis' Impact on Korea and Dooley and Hutchison (2009) for the effect the sub-prime market has on the developing world.)

[17] While Hartarska and Nadolnyak (2007) found small boards to lead to better financial performance, Mersland and Strom (2009) were unable to conclude with the same results.

The governance literature on microfinance institutions has found no significant results with regulation, Hartarska and Nadolnyak (2007), Mersland and Strom (2009), and Barth et. al (2004), in the traditional banking literature, yet women CEOs, local directors, smaller board sizes, internal auditors, and monitoring improved the operating cost of the microfinance institutions and banks. While neither Hartarska and Nadolynyak (2007) or Barth et. al (2004) found significant results with regulation in cross-country studies of MFI and banks respectively, this study has filled a major gap in the literature concluding that non-profits operate most efficiently to reach the poor compared with the more costly production of regulated entities.

Economies of scale were found by Zacharias (2008) with MixMarket data, however, his results are not published and his technique is a simple ANACOVA model. Scale values are found by Ahmad (2009), who uses DEA analysis and not the translog SUR framework applied in this study and used in much of the commercial banking literature. The scale value is expected to be less than one as "the small principal amounts inherent with microcredit leave little economies of scale in the lending process to cover fixed costs" (Brau and Woller, 2004).

Caudill, Gropper, and Hartarska (2009) do not find economies of scale for their sample of MFIs but they uniquely allow the unobservables in their data to segment the sample into cost efficient firms from inefficient firms. They use a two stage mixture model approach to show that over time NGOs and Central Asian MFIs are not cost reducing over time[19]. The first stage uses a technique which segments the sample into cost efficient MFIs from less efficient MFIs with controls for age to capture possible learning by doing. The second stage auxiliary equations use control variables to explain the probability that an MFI belongs to the regime of MFIs who improve their efficiency in time and those that do not.

[19] This finding differs from Zacharias (2008), an online study, who finds NGOs to be more efficient over time and differs from this study, although the results of this study present a cross-sectional view.

Nawaz (2009) uses DEA on MixMarket data to find scale values in both a constant and variable returns to scale framework.[20] His primary purpose of calculating scale values on each MFI in his sample is to determine how inefficient each MFI would be without subsidation.[21] He calculates the subsidy dependence index proposed by Yaron (1992a) and modified by Morduch et al (2005), and concludes that Central Asian and Eastern European MFIs do not enhance public wealth.

Some studies, such as Hermes et al (2008), test to see if a trade-off exists between outreach and efficiency as smaller loans should have higher transaction cost due to additional screening and monitoring. The authors use SFA to control for measurement error and any deviation from the best practice MFI reveals technical inefficiency. Traditional variables used in prior studies, such as the ALB (average loan balance), the ASB (average saving balance), and the number of borrowers show that reaching poorer borrowers increases the inefficiency of the MFI and that reaching fewer borrowers results in inefficiency as it pertains to a lack of scale as shown in this paper. More woman borrowers seemed to increase inefficiency as women generally constitute poorer clients.[22]

Scale efficiency studies on traditional banks can provide incites on how efficiencies or inefficiencies can be found with microfinance data. One analysis, by Huang and Wang (2001) uses a stochastic cost frontier model to incorporate both technical and allocative inefficiencies, a fixed effect model to allow for technical inefficiency only, and a conventional model which ignores both. The SFA and conventional method both showed that as the bank size increases, on

[20] The variable returns to scale framework is appropriate for non-competitive markets, however the translog cost function used in this study assumes some market power in the output market (Varian, 1984).
[21] Nawaz (2009) clearly fills a gap in the literature with respect to subsidation. He removes subsidies from the MFIs found to negatively distort public wealth, but he finds some to be clearly inefficient without the subsidies. His analyses is substantial but a bit unclear as in some models the subsidies seem to drive the MFI to scale which would presumably enhance public wealth.
[22] The results in **Table 6** show that woman may actually enhance efficiency (actually, it may be 50/50 between male and female, due to scale). Nawaz (2009) finds that women enhance efficiency with subsidized MFIs.

the sample of Taiwanese banks, that economies of scale are realized, while the fixed effect model results does not follow the same pattern.

Kenjegalieva et. al (2009) measure the efficiency of 13 banking systems in the Central and Eastern European region by including risk to ensure that banking efficiency is not misrepresented by underfunding of loan monitoring and risk assessment systems. Inclusion of risk minimization is extremely important in banking efficiency models and should be included before any policy prescriptions are made. Their results show that the 8 countries that joined the EU in May 2004 and the 2 negotiating countries were found to be less efficient than the Moldovan, Russian, and Ukrainian banks,[23] which showed higher levels of efficiency than the sample means for all of the three input/output specifications, the intermediation, production, and profit-revenue based approaches, under the technical efficiency evaluation.

Section 2. The Estimation Approach

The estimation approach is similar to that of the first essay of the dissertation, using the translog cost model with 2 input share equations and the SUR technique[24]. However, the last study specified three inputs of production (labor, physical capital, and financial capital), the physical capital input share equation was dropped from the SUR system in order to estimate the system, and total cost, the price of labor, and the price of financial capital were mean scaled, divided by the price of physical capital, and the natural log was taken.

[23] The authors mention that these are the Commonwealth of Independent States which neighbor the EU countries and are the most efficient despite the severe recessions that they have faced. However, the high efficiency found was lessened in the risk adjusted models for these countries under the intermediation approach.
[24] The estimation was performed in STATA 9.2.

As the MixMarket data set includes only 2 inputs (salary and ccost),[25] both input share equations are included in the estimation of the SUR system. Therefore, total cost, and the two input prices are mean scaled and the natural log is then taken. The translog cost model estimated is shown below, with two outputs (either number of borrowers & number of savers or volume of loans & volume of savings, for a robustness check):

$$\ln(C) = \alpha_0 + \sum_{1}^{2} \alpha_1 \ln(p_1) + \sum_{1}^{2} \beta_1 \ln(y_1) + \frac{1}{2}\sum_{1}^{2} \gamma_{11} \ln(p_1)\ln(p_1) + \frac{1}{2}\sum_{1}^{2}\sum_{1}^{2} \delta_{11} \ln(y_1)\ln(y_1) + \kappa_{12} \ln(p_1)\ln(p_2) + \sum_{1}^{2}\sum_{1}^{2} \rho_{11} \ln(p_1)\ln(y_1) + \ln u \quad (1)$$

where C is total cost, p_1 is the cost of financial expenditure per liability, p_2 is operating expense per employee, y_1 is the number of borrowers or the volume of loans, y_2 (used occasionally) is the number of savers or the volume of savings; $\alpha, \beta, \gamma, \delta, \kappa, and\ \rho$ are parameters to be estimated, and ln u is normally distributed.

One output models were also estimated for the entire sample, in **Table 1**, for the small MFIs in the sample, **Table 2**, for the large MFIs in the sample, **Table 3**, for the MFI types, **Table 4,** for the regions, and **Table 5** with additional control variables (the write-off ratio, percent of women, and proportion of the population below poverty). **Table 1**, **Table 2**, and **Table 3** shows the one output models in terms of number of borrowers in Column 1 and volume of loans in Column 3. Scales are found on MFI types in **Table 4** in terms of number of borrowers.

[25] Salary is defined as operating expense per employee which includes the salary and physical capital per employee and Ccost is financial expenditure per liability.

The translog cost model was estimated with homogeneity and symmetry restrictions, along with the two input share equations on labor and financial capital. Here are the restrictions imposed on the system:

$$\alpha_1 + \alpha_2 = 1, \gamma_{11} + \kappa_{12} = 0, \ \gamma_{22} + \kappa_{12} = 0, \ \rho_{11} + \rho_{21} = 0, \ \rho_{12} + \rho_{22} = 0 \qquad (2)$$

The two input shares estimated with eq. (1) are:

$$\text{Finance Share} = dlnC/dlnp_1 = \alpha_1 + \gamma_{11} ln\,(p_1) + \kappa_{12}\ ln\,(p_2) + \rho_{11} ln\,(y_1) + \ln u^{26} \qquad (3)$$

$$\text{Labor Share} = dlnC/dlnp_2 = \alpha_2 + \gamma_{22} ln\,(p_2) + \kappa_{12}\ ln\,(p_1) + \rho_{21} ln\,(y_1) + \ln u \qquad (4)$$

A symmetry condition is imposed across the two input share equations [eq. (3) and eq.(4)]

$$\kappa_{12} = \kappa_{12} \qquad (5)$$

Since the variables are mean-scaled, the scale value with respect to number of borrowers (y1) or volume of loans (loanport), is the coefficient on each of these variables, respectively. In the case of the double output models, whether number of borrowers & number of savers or loan volume & volume of savings, the scale value is found by adding the coefficients on each of the respective variables. Economies of scale means that as output increases by one percent, total cost increases less than proportionately. In this circumstance, the MFI would benefit by extending additional loans and/or collecting additional savings because with increased output, total cost/loan would fall. This will provide the MFI with more profit in the short run and lower the interest rate on loans in the long run.

[26] This specification is for a one output model (a two output model would include the additional output, either number of savers or volume of savings).

This study finds scale economies on a substantial number of observations (over 1,000 MFIs) using the largest MixMarket data set available. Scale economies are found using a SUR technique with a translog cost model and two input share equations, representing salary (operating expense per employee) and ccost (financial expenditure per liability). Total cost and the two input prices are mean scaled and the natural log is taken.

Section 3: Data description

Table 2.1

Variable	Explanation	Obs	Mean	Std. Dev.	Min	Max
Ccost	**Cost of Financial Expenditure to Liability**	3170	0.10	0.12	0.00004	0.89
Salary	**Operating Expense per Employee**	3170	12,591	9,505	143	50,721
TC	**Total Cost**	3170	2,560,364	5,193,340	24.47	66,900,000
y1	**Number of Borrowers**	3170	25,796	63,416	9	989,641
y2	**Number of Savers**	1270	33,424	67,854	1	559,161
loanport	**Volume of Loans**	3170	11,300,000	25,600,000	28	305,000,000
volunsav	**Volume of Savings**	1270	10,600,000	24,100,000	44	177,000,000
woff	**Write Off for Past 12 Months**	2122	0.02	0.05	0.01*	0.7126
pwomen	**Females per Net Asset Balance**	3135	0.60	0.31	0	1
botpv	**Client Bottom Half of Population Below Poverty Line**	2621	0.04	0.15	0	1

*** Note that the average of the client bottom half of the population below the poverty line is only 4%.**

This table demonstrates the extensiveness of this data sample with respect to the number of observations provided. The MFIs have gone so far as to provide the write off ratio, along with the females per net asset balance, and clients in the bottom half of the population below the poverty line. The data offered to the MixMarket are self-reported and an MFI has a 3 star rating if it has at least two years of financial and outreach data reported or 4 stars if its financial statements are audited. The MFIs in this essay are much larger than the MFIs in the first study as the mean loan volume in the first essay was only $3,467,519 compared with the $11,300,000

value here and the savings volume average was a mere $460,418 compared with the $10,600,000 here. The outreach of these MFIs is on average three times the outreach found in the first essay as the scale has allowed for this and the number of savers is 15 times the number of savers found in the first essay. There are 71 Rural Banks[27], 946 NGOs, 622 NBFIs (non-bank financial institutions), and 421 Coops. Since the data set was limited to only 71 Rural Banks, the efficiency results are not representative of the population to the degree of the NGOs. The largest global data set on the operational characteristics of MFIs as of November 2008 was graciously provided by the MixMarket Exchange. The Microfinance Information eXchange (the MIX) is a non profit, private organization that aims to promote information exchange in the microfinance industry. Its goal is to promote financial transparency and help build the information infrastructure in developing countries.

Section 4. Discussion of Empirical Results

In the first essay, scale values and input price elasticities were computed on a sample of 650 MFIs from a dataset of rated MFIs with the conclusion that collecting savings along with loan extension drives the MFI towards efficiency and that MFIs are driven to scale less by outreach but more by higher loan volume, noted by Hermes et. al (2008) in the tradeoff of outreach vs. sustainability. The large MFIs in the sample were more efficient, in terms of scale than the small MFIs, both in the model with output measured by the number of borrowers, and the output measured by the volume of loans, but much more efficient in terms of loan volume than number of borrowers. Loan volume increased the large MFI's scale by 24% while number of borrowers increased the scale by only 9.8%

[27] The Rural Banks in the sample are found in East Asia and the Pacific, South Asia, and Africa.

The SUR technique assumes cost minimization while we focus on the main objective of MFIs, the number of borrowers reached. The scale value for the one output model with number of borrowers as the output is 0.80. A robustness check is performed, using volume of loans as the output, which shows the scale value to be 0.88. This could indicate that MFIs are reaching scale by higher average loan balances as reaching poorer borrowers is costlier as average loan balances are small compared to the more intensive screening and monitoring necessary.

The results indicate that loan volume drives scale over number of borrowers, while number of savers, in addition to number of borrowers improves scale. When the sample is split between the small and large MFIs, I find that the small MFIs are at approximately 60% of their capacity in terms of outreach (0.56) compared to the large MFIs (0.85). Number of savers included with number of borrowers enhances efficiency for the small and large MFIs while volume of savings with volume of loans only enhances efficiency for the small MFIs. The result is contained in **TABLE 4** which shows the economies of scale on institutional types. NGOs are the closest to constant returns to scale and only offer loans while Coops offer savings and time deposits, Non-bank financial institutions offer wholesale certificates of deposits, and Rural banks offer savings deposits and money transfers and are the only types out of the 4 to be supervised by a banking authority, although these type institutions only exists in one country.[28] The small MFIs appear to be reaching scale through volume of loans over number of borrowers much more than the large MFIs.[29]

This result seems contradictory to expectations, as one would expect small MFIs to maintain more of a focus on outreach to the very poor while **Table 2.4** shows that larger MFIs are almost equally driven to scale by loan volume and number of borrowers. This could be

[28] IMF: In Chapter 7: Rural and Microfinance Institutions: Regulatory and Supervisory Issues
[29] This conclusion is in line with the graph in Zacharias (2008) which shows that some small MFIs produce efficiently.

reflective of the "mission drift" hypothesis as perhaps most loans extended by the large MFIs are of a higher average loan balance or perhaps the higher scale reached by volume of loans by the large MFIs allows the large MFIs to more effectively reach a larger number of borrowers.

I apply the same SUR framework to the MFI types in the sample (Rural, NGO, Non-bank financial institution, and Coop). The results show that Rural banks are operating most inefficiently. Out of the four MFIs types, NGOs are operating most efficiently with a scale value of 0.86. The COOPs in this sample are operating relatively more efficiently than the Non-bank financial institutions but less efficiently than the NGOs. These results are comparable to the study by Zacharias (2008), as he finds NGO scale at 0.84 and Non-NGO scale at 0.71 for observations from 2004 and 2005.

Scale values by regions indicate that Africa has achieved the highest scale when output is measured by the number of borrowers, i.e. in terms of outreach, while Eastern European and Central Asian MFIs show efficiency in outreach (both in terms of number of borrowers and number of borrowers and savers). Additionally, Eastern Europe and Central Asian MFIs are the most efficient in terms of loan volume and African MFIs have the most economies of scale. As there are insufficient observations in the number of borrower and savers and volume of loans and volume of savings categories for the Middle East and North Africa, this could very well indicate less NGOs (deposit taking institutions) in this region. Future research should address why Eastern European and Central Asian MFIs operate most efficiently and why most gains stand to come from funds channeled to Africa and South Asia.

When additional explanatory variables, such as the write-off ratio, percentage of women, and proportion of loans extended to the bottom half of clients below the poverty line, are added to the system of cost and input share equations, the results show that the extension of loans to

women may enhance efficiency while extension of loans to the poor may reduce efficiency. However, since MFIs seek a double bottom line with the first mission on outreach to the poorest but productive workers and the second mission on sustainability, MFIs are willing to accept some inefficiency as profit maximization alone would leave the "unbankable", unbankable. Additionally, the independent variables show that as cost increases by one percent that the write-off ratio increases cost by 1.13%, and that women decrease cost by 0.53%.

This essay demonstrates an efficiency analysis study with regard to microfinance regional efficiency, organizational type, size, and additional control variables. The analysis parallels that of the commercial banking literature in the non-frontier system arena. Eastern European and Central Asian MFIs were found to be operating most efficiently, however they may not be cost reducing over time, as this is only a cross-sectional analysis, as demonstrated by Nawaz (2009) and Caudill, Gropper, and Hartarska (2009). While Hermes et. al (2008) finds that women reduce the efficiency of the MFIs as they constitute poorer borrowers, other studies have found that woman are fiscally responsible. As NGOs are beginning to transfer money and accept deposits, this analysis suggests that this extension of activities will promote development in these countries as the NGOs in the sample were found to operate more efficiently than the other three institutional types.

Table 2.2
Mix Market Data
Entire Sample

Cost1	One Output (Y1)	Two Outputs (Y1 and Y2)	Cost1	One Output (Loanport)	Two Outputs (Loanport &Volunsav)
	Coefficient	Coefficient		Coefficient	Coefficient
CCost1	0.0693***	0.0772***	CCost1	0.5609***	0.5663***
Salary1	0.9307***	0.9228***	Salary1	0.4391***	0.4337***
Y1a	**0.7997*** **	**0.6543*** **	Loanport1	**0.8771*** **	**0.7763*** **
Y2a		**0.1769*** **	LoanportLoanport	0.0587***	0.1268***
Y1Y1	0.0624***	0.0773***	Volunsav1		**0.0765*** **
Y2Y2		0.0771***	VolunVolun		0.0671***
Y1Y2		-0.0900***	LoanportVol		-0.1661***
CcostCcosta	0.0100**	-0.0035	CcostCcosta	0.1426***	0.1314***
SalarySalarya	0.0100**	-0.0035	SalarySalarya	0.1426***	0.1314***
Y1Salary	0.0115**	0.0128	LoanSalary	-0.0568***	-0.0488***
Y1Ccost	-0.0115**	-0.0128	LoanCcost	0.0568***	0.0488***
Y2Salary		0.0033	VolSalary		0.0091
Y2Ccost		-0.0033	VolCCost		-0.0091
SalaryCcost	-0.0100**	0.0035	SalaryCcost	-0.1426***	-0.1314***
Constant	0.1235***	0.1048***	Constant	0.1681***	0.2038***
Labor Share					
Ccost1	-0.1198***	-0.1433***	Ccost1	-0.1411***	-0.1824***
Salary1	0.0525***	0.0449***	Salary1	0.0672***	0.0700***
Y1a	0.0132***	0.0378***	Loanport1	-0.0364***	0.0159**
Y2a		-0.0145**	Volsav1		-0.0443***
Constant	-0.1026***	-0.1658***	Constant	-0.1690***	-0.2549***
Finance Share					
Ccost1	1.5666***	1.6528***	Ccost1	1.5874***	1.6710***
Salary1	-0.1198***	-0.1433***	Salary1	-0.1411***	-0.1824***
Y1a	0.0363***	-0.0456***	Loanport1	0.1399***	0.0128
Y2a		0.0866***	Volsav1		0.1137***
Constant	-0.3544***	-0.1096***	Constant	-0.2127***	0.0478**
N	**2620**	**1094**		**2620**	**1092**
Cost r-square	**0.8697**	**0.8980**		**0.8719**	**0.9074**
Labor r-square	**0.2211**	**0.3370**		**0.2545**	**0.3637**
Finance r-square	**0.8527**	**0.9054**		**0.8695**	**0.9199**
Economies of Scale	**0.7997**	**0.8312**		**0.8771**	**0.8528**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings)
(e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0

Table 2.3
Mix Market Data (Sorted by Asset Size)
Small MFIs in the Sample (1-2481)

Cost1	One Output (Y1)	Two Outputs (Y1 and Y2)	Cost1	One Output (Loanport)	Two Outputs (Loanport &Volunsav)
	Coefficient	Coefficient		Coefficient	Coefficient
CCost1	0.2181***	0.2745***	CCost1	0.4398***	0.4513***
Salary1	0.7819***	0.7255***	Salary1	0.5602***	0.5487***
Y1a	**0.5546*** **	**0.4381*** **	Loanport1	**0.7224*** **	**0.7823*** **
Y2a		**0.1171*** **	LoanportLoanport	0.0758***	0.2014***
Y1Y1	0.0596***	0.0780***	Volunsav1		**-0.0284**
Y2Y2		0.0879***	VolunVolun		0.0309**
Y1Y2		-0.1029***	LoanportVol		-0.2085***
CcostCcosta	-0.0189***	-0.0265***	CcostCcosta	0.0711***	0.1010***
SalarySalarya	-0.0189***	-0.0265***	SalarySalarya	0.0711***	0.1010***
Y1Salary	-0.0299***	-0.0464***	LoanSalary	-0.0406***	0.0113
Y1Ccost	0.0299***	0.0464***	LoanCcost	0.0406***	-0.0113
Y2Salary		0.0231**	VolSalary		-0.0575***
Y2Ccost		-0.0231**	VolCCost		0.0575***
SalaryCcost	0.0189***	0.0265***	SalaryCcost	-0.0711***	-0.1010***
Constant	0.2656***	0.0888**	Constant	0.0099	-0.0150
Labor Share					
Ccost1	-0.1253***	-0.1823***	Ccost1	-0.1180***	-0.2039***
Salary1	0.0555***	0.0484***	Salary1	0.0565***	0.0856***
Y1a	0.0582***	0.0792***	Loanport1	-0.0155*	0.0021
Y2a		-0.0210**	Volsav1		-0.0766***
Constant	-0.0901***	-0.2069***	Constant	-0.1316***	-0.2650***
Finance Share					
Ccost1	1.5097***	1.6640***	Ccost1	1.4595***	1.6447***
Salary1	-0.1253***	-0.1823***	Salary1	-0.1180***	-0.2039***
Y1a	-0.1017***	-0.1699***	Loanport1	0.0526**	-0.0178
Y2a		0.1081***	Volsav1		0.1908***
Constant	-0.4451***	-0.1619***	Constant	-0.3764***	-0.0497
N	**1191**	**451**		**1191**	**466**
Cost r-square	**0.8093**	**0.8062**		**0.7325**	**0.8056**
Labor r-square	**0.2504**	**0.3697**		**0.1827**	**0.3963**
Finance r-square	**0.8153**	**0.8923**		**0.8092**	**0.8978**
Economies of Scale	**0.5546**	**0.5552**		**0.7224**	**0.7539**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings)
(e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0

Table 2.4
Mix Market Data (Sorted by Asset Size)
Large MFIs in the Sample (2482 - 4961)

Cost1	One Output (Y1)	Two Outputs (Y1 and Y2)	Cost1	One Output (Loanport)	Two Outputs (Loanport &Volunsav)
	Coefficient	Coefficient		Coefficient	Coefficient
CCost1	0.0889***	0.0846***	CCost1	0.5799***	0.6036***
Salary1	0.9111***	0.9154***	Salary1	0.4201***	0.3964***
Y1a	**0.8478*** **	**0.6379*** **	Loanport1	**0.9055*** **	**0.6524*** **
Y2a		**0.2524*** **	LoanportLoanport	0.0951***	0.1072***
Y1Y1	0.0907***	0.1084***	Volunsav1		**0.2024*** **
Y2Y2		0.0616***	VolunVolun		0.0769***
Y1Y2		-0.0768***	LoanportVol		-0.1095***
CcostCcosta	0.0650***	0.0597***	CcostCcosta	0.1364***	0.1505***
SalarySalarya	0.0650***	0.0597***	SalarySalarya	0.1364***	0.1505***
Y1Salary	0.0411***	0.0450***	LoanSalary	-0.0566***	-0.0685***
Y1Ccost	-0.0411***	-0.0450***	LoanCcost	0.0566***	0.0685***
Y2Salary		0.0060	VolSalary		0.0203**
Y2Ccost		-0.0060	VolCCost		-0.0203**
SalaryCcost	-0.0650***	0.0597***	SalaryCcost	-0.1364***	-0.1505***
Constant	0.2617***	0.5293***	Constant	-0.0087	-0.1043**
Labor Share					
Ccost1	-0.1487***	-0.1677***	Ccost1	-0.1597***	-0.1814***
Salary1	0.0745***	0.0607***	Salary1	0.0776***	0.0990***
Y1a	0.0127**	0.0364***	Loanport1	-0.0478***	0.0104
Y2a		-0.0197***	Volsav1		-0.0454***
Constant	-0.1116***	-0.1929***	Constant	-0.1950***	-0.2652***
Finance Share					
Ccost1	1.6230***	1.6821***	Ccost1	1.6348***	1.6479***
Salary1	-0.1487***	-0.1677***	Salary1	-0.1597***	-0.1814***
Y1a	0.0411***	-0.0626***	Loanport1	0.1858***	-0.0440**
Y2a		0.0667***	Volsav1		0.0777***
Constant	-0.3509***	-0.1070***	Constant	-0.1897***	-0.0347
N	**1682**	**713**		**1682**	**742**
Cost r-square	**0.8170**	**0.8732**		**0.7550**	**0.8595**
Labor r-square	**0.2929**	**0.3590**		**0.3246**	**0.3874**
Finance r-square	**0.8971**	**0.9262**		**0.9123**	**0.9343**
Economies of Scale	**0.8478**	**0.8903**		**0.9055**	**0.8548**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings)
(e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0

Table 2.5
Mix Market Data (Sorted by Institutional Type)
Scale Economies with One Output (Y1 – Number of Borrowers)[30]

Cost1	Rural	NGO (Non-Profit)	Non-Bank Fin. Inst	Coop
	Coefficient	Coefficient	Coefficient	Coefficient
CCost1	0.1392**	0.1499***	0.0751***	0.1628***
Salary1	0.8608***	0.8501***	0.9249***	0.8372***
Y1a	**0.6519*** **	**0.8612*** **	**0.7232*** **	**0.7801*** **
Y2a				
Y1Y1	0.0603	0.0694***	0.0533***	0.0588***
Y2Y2				
Y1Y2				
CcostCcosta	-0.0703**	-0.0189*	0.0216**	0.0428**
SalarySalarya	-0.0703**	-0.0189*	0.0216**	0.0428**
Y1Salary	0.0192	-0.0037	0.0221**	-0.0012
Y1Ccost	-0.0192	0.0037	-0.0221**	0.0012
Y2Salary				
Y2Ccost				
SalaryCcost	0.0703**	0.0189*	-0.0216**	-0.0428**
Constant	0.0788	0.7530***	0.0097	-0.4229***
Labor Share				
Ccost1	0.0323	-0.1173***	-0.0899***	-0.1855***
Salary1	0.0149	0.0432***	0.0498***	0.0513***
Y1a	0.1288***	-0.0103**	-0.0072	-0.0026
Y2a				
Constant	-0.0535	-0.1174***	-0.1458***	-0.1721***
Finance Share				
Ccost1	1.3188***	1.5122***	1.5673***	1.7218***
Salary1	0.0323	-0.1173***	-0.0899***	-0.1855***
Y1a	-0.0863**	0.0783***	0.1391***	0.0875***
Y2a				
Constant	-0.3295***	-0.1670***	-0.4111***	-0.2797***
N	**71**	**946**	**622**	**421**
Cost r-square	**0.9388**	**0.8784**	**0.8330**	**0.8745**
Labor r-square	**0.1640**	**0.1717**	**0.1894**	**0.3905**
Finance r-square	**0.8856**	**0.8045**	**0.8657**	**0.9436**
Economies of Scale	**0.6519**	**0.8612**	**0.7232**	**0.7801**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings), (e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0

[30] This regression includes outliers. The first paper only took out the top 1% outliers on total cost and input prices.

Table 2.6
Mix Market Data (Sorted by Region) – Dropped Top Outliers (Above 99%)

	Africa	Latin America	Middle East & N. Africa
Y1	**Scale = 0.7282** N = 519 Cost r-square = 0.8356 Labor r-square = 0.1970 Finance r-square = 0.8436	**Scale = 0.8538** N = 616 Cost r-square = 0.8637 Labor r-square = 0.2253 Finance r-square = 0.8788	**Scale = 0.8502** N = 110 Cost r-square = 0.8513 Labor r-square = 0.4210 Finance r-square = 0.9015
Y1 & Y2	**Scale = 0.8222** N=351 Cost r-square = 0.9126 Labor r-square = 0.3524 Finance r-square = 0.9024	**Scale = 0.9499** N= 228 Cost r-square = 0.9139 Labor r-square = 0.5368 Finance r-square = 0.9428	**Insufficient Obs.**
Loanport	**Scale = 0.8060** N=519 Cost r-square = 0.8979 Labor r-square = 0.2118 Finance r-square = 0.8567	**Scale = 0.8571** N = 616 Cost r-square = 0.9065 Labor r-square = 0.3265 Finance r-square = 0.9035	**Scale = 0.8923** N = 110 Cost r-square = 0.6929 Labor r-square = 0.4613 Finance r-square = 0.9005
Loanport & Volunsav	**Scale = 0.8901** N=349 Cost r-square = 0.9402 Labor r-square = 0.3788 Finance r-square = 0.9175	**Scale = 0.9111** N = 229 Cost r-square = 0.9231 Labor r-square = 0.5522 Finance r-square = 0.9442	**Insufficient Obs.**
	Eastern Europe/C. Asia	**South Asia**	**East Asia & the Pacific**
Y1	**Scale = 1.0158** N = 326 Cost r-square = 0.8711 Labor r-square = 0.2680 Finance r-square = 0.8300	**Scale = 0.7684** N = 267 Cost r-square = 0.9220 Labor r-square = 0.2222 Finance r-square = 0.9095	**Scale = 0.8222** N = 207 Cost r-square = 0.8504 Labor r-square = 0.3588 Finance r-square = 0.8396
Y1 & Y2	**Scale = 1.1286** N=74 Cost r-square = 0.8730 Labor r-square = 0.3545 Finance r-square = 0.9184	**Scale = 0.7619** N= 79 Cost r-square = 0.9332 Labor r-square = 0.2375 Finance r-square = 0.9471	**Scale = 0.8892** N= 119 Cost r-square = 0.8829 Labor r-square = 0.4988 Finance r-square = 0.8786
Loanport	**Scale = 0.9789** N=326 Cost r-square = 0.9039 Labor r-square = 0.2634 Finance r-square = 0.8441	**Scale = 0.9101** N = 267 Cost r-square = 0.9113 Labor r-square = 0.2460 Finance r-square = 0.9138	**Scale = 0.9352** N = 207 Cost r-square = 0.8350 Labor r-square = 0.1135 Finance r-square = 0.8047
Loanport & Volunsav	**Scale = 1.1692** N=72 Cost r-square = 0.9162 Labor r-square = 0.3920 Finance r-square = 0.9264	**Scale = 0.7767** N = 79 Cost r-square = 0.9018 Labor r-square = 0.1732 Finance r-square = 0.9468	**Scale = 0.9471** N = 119 Cost r-square = 0.8905 Labor r-square = 0.4695 Finance r-square = 0.8638

This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings), (e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0 (symmetry condition)

Table 2.7
Mix Market Data – Entire Sample with 12 month Write Off, Percent of Woman, and Client Bottom Half of Population Below Poverty Line

Cost1	With Write-Off	Percent of Women	Bottom Half	Write-Off, Women, Botpv
	Coefficient	Coefficient	Coefficient	Coefficient
CCost1	0.0744***	0.1036***	0.0676***	0.0966***
Salary1	0.9256***	0.8964***	0.9324***	0.9034***
Y1a	**0.7948*** **	**0.8195*** **	**0.7939*** **	**0.7978*** **
Y1Y1	0.0488***	0.0617***	0.0628***	0.0412***
CcostCcosta	0.0222***	0.0111**	0.0109**	0.0243***
SalarySalarya	0.0222***	0.0111**	0.0109**	0.0243***
Y1Salary	0.0221***	0.0062	0.0098**	0.0172**
Y1Ccost	-0.0221***	-0.0062	-0.0098**	-0.0172**
SalaryCcost	-0.0222***	-0.0111**	-0.0109**	-0.0243***
Woff	1.1049***			1.1308***
Pwomen		-0.5016***		-0.5330***
Botpv			-0.0009	-0.0006
Constant	0.1528***	0.4436***	0.0869***	0.4497***
Labor Share				
Ccost1	-0.1139***	-0.1205***	-0.1145***	-0.1024***
Salary1	0.0515***	0.0517***	0.0476***	0.0384***
Y1a	0.0061*	0.0118***	0.0163***	0.0053
Constant	-0.1031***	-0.1030***	-0.0869***	-0.0794***
Finance Share				
Ccost1	1.5586***	1.5679***	1.5622***	1.5536***
Salary1	-0.1139***	-0.1205***	-0.1145***	-0.1024***
Y1a	0.0564***	0.0394***	0.0322***	0.0660***
Constant	-0.3475***	-0.3544***	-0.3970***	-0.4076***
N	**1780**	**2571**	**2058**	**1243**
Cost r-square	**0.8498**	**0.8826**	**0.8678**	**0.8619**
Labor r-square	**0.2264**	**0.2196**	**0.2104**	**0.2129**
Finance r-square	**0.8564**	**0.8522**	**0.8488**	**0.8551**
Economies of Scale	**0.7948**	**0.8195**	**0.7939**	**0.7978**

* significant at 10% level; ** significant at 5% level; ***significant at 1% This estimation takes into account the linear homogeneity and the consequent restrictions: (a) [Cost1]Ccost1 + [Cost1]Salary1 = 1, (b) [Cost1]CcostCcosta + [Cost1]SalaryCcost = 0, (c) [Cost1]SalarySalarya + [Cost1]SalaryCcost = 0, (d) [Cost1]Y1Salary + [Cost1]Y1Ccost = 0, (where Y1 = number of borrowers, Y2 = number of savers, Loanport = Volume of Loans, Volunsav = Volume of Savings)
(e) [LaborShare2]Ccost1 - [FinanceShare2]Salary1 = 0

Chapter 3

The Influence of Off-Balance Sheet Activity on Community Development Bank Production and this Efficiency Compared to Microfinance Production Abroad

There are 2 main purposes of this essay. The first and most important purpose is to estimate the efficiency of 32 U.S. Community Development Banks in 2009 with the inception of TARP, as these banks borrowed funds, and the second mission is to compare the efficiency of the banks with the scales of the Microfinance Institutions abroad found in the second essay. The analysis finds that this sample of Community Development Banks is more efficient in June 2009 than they were leading up to the crisis in June 2006. Secondly, inclusion of a second output, NII, non-interest income, into the SUR translog cost system, highlights the influence of off-balance sheet activity in the production inefficiency in June 2006 prior to the crisis, to my knowledge, not documented yet in the empirical literature. While production inefficiency is also found in 2009 from off-balance sheet activity, the inefficiency gap is more conservative in 2009 than it was in 2006. This study highlights the lesser TARP distributions to small banks compared to the large investment banks and compares the domestic production of these banks to the international production of the MFIs, microfinance institutions, abroad. The industry scale of these U.S. institutions is most comparable to the regional scale found with the Latin American Microfinance Institutions in the second essay once off-balance sheet activity is taken into account.

The first two essays of the dissertation used the SUR translog cost model to estimate efficiency of rated MFIs and MFIs that reported to the Mix Market Exchange. This essay will measure the efficiency of the small number of U.S. Community Development Banks with annual

data including the fourth quarter of 2008 to the third quarter of 2009, using the same 3 inputs used in the first essay (labor, physical capital, and financial capital) but efficiency will also be estimated with a fourth input, the expense of federal funds purchased, interest on trading liabilities, and other borrowed money to capture any change in efficiency related to this variable. The results show that by adding the fourth input, the scale falls only from 0.9725 to 0.9592. This result implies that these banks weathered the storm of the 2007 crisis, however, it is unclear how much TARP[31] played in the process.

Apart from estimating the annual efficiency, the fourth quarter of 2008 to the third quarter of 2009, with 3 inputs and one output (labor, physical capital, financial capital, and loan volume) and four inputs and one output (labor, physical capital, financial capital, borrowed funds, and loan volume), this study also calculates the efficiency with 4 inputs and 2 outputs (loan volume and NII, non-interest income, a proxy for off-balance sheet activity). The results show that by adding NII, the Community Development Banks operate substantially less efficiently in 2006 while when adding NII the impact in 2009 is adverse but more subtle; however as Casu and Girardone, 2005, point out, NII may overestimate the amount of off-balance sheet activity, since fees and commissions also come from on-balance sheet activity.

The second output, NII, improves the explanatory power of the cost and input share equations, especially the finance and borrowed share equations, therefore, the equation would be misspecified without this variable. The scale value for June 2006 without NII, the value found in the lower left hand column of **Table 3**, suggest that these banks were less efficient than in June 2009. Yet, when NII is taken into account, the consequences of the off-balance sheet activity in 2006 are far more adverse than in 2009. This result suggests that perhaps the bank managers are trying to be more cautious as a result of the 2007 crisis.

[31]TARP is funds created in 2008 to buy assets from troubled banks at low capital cost.

An efficiency estimate between 0.84 and 0.98, or 0.91 to be exact, seems reasonable as the first essay demonstrated that the rated MFIs, or smaller MFIs, operated at 0.75 with 650 observations, and the second essay revealed the larger Mix Market MFIs to operate at 0.85. While the U.S. banks represent a developed nations' MFI, the scale value seems accurate, showing more conservative management practices in 2009 after the over indebtedness shown with the large inefficient scale value in 2006 with NII.

Section 1: Literature Review: What is a CD Bank and Why is proxying for Off-Balance Sheet Activity Important?

Community development financial institutions (CDFIs) are financial intermediaries that include community development loan funds, community development credit unions, microenterprise development organizations, venture capital funds, and community development banks (Cascade, Winter 1999). Most CDFIs (community development financial institutions) are unregulated non-profits. They are the developed nation's counterparts to MFIs (microfinance institutions) in developing countries. These institutions serve low income groups and support affordable housing, community infrastructure, and small business activity.

A community development bank is a Federal Deposit Insurance Corporation – insured bank or thrift that has a primary mission of promoting community development.[32] These banks are similar to MFIs in that they offer financial services to the underserved communities. Community Development Banks must demonstrate that 60% of their "lending, services, and other activities benefit low income communities." They are commercial banks as they collect deposits and make loans. Their loans support small businesses, community facilities, affordable

[32] See www.cdbanks.org

housing, and most are privately held. The first U.S. Community Development Bank was established in 1973, the Shore Bank in Chicago, IL.

CDFIs secure funding from a variety of sources, about a fifth from banks, foundations, governments, religious institutions, and to a lesser extent from individuals according to year-end data from 1998 (Cascade, Winter 1999). One example is the Community Loan Fund in Concord, New Hampshire, which trains former welfare recipients to be in-home health care providers. They provide public funds to secure safer neighborhoods, to aid in the missions of religious organizations, community activities (e.g. dance studios), and support education for minorities. The largest U.S. community development support organization, LISC – Local Initiatives Support Corporation, was organized in 1979 by the Ford Foundation, which also supports international microfinance activity.

The Community Development Sector is strong in the U.S. and has been for 10 years. It is largely based on private investment while community development in the UK is based on the public sector through the Phoenix Fund, a fund that supports innovative ways of supporting enterprise in deprived areas; it began in 1997 through the European Union. CDFIs are evaluated on a double or triple bottom line, with profitability, community development, and environmental conservation all important objectives. Social investors, whether private individuals, charitable foundations, religious institutions or government agencies, who seek both financial and social performance indicators are willing to trade return on investment for business development services, such as marketing and technology transfers, improvement in quality of life, such as productivity and empowerment, and job creation (Kneiding and Tracey, 2009).

Realistically, however, while the importance of microfinance institutions abroad and U.S. Community Development Financial Institutions can not be understated, the issue of excessive

risk-taking through off-balance sheet activity must be kept in check to prevent a relapse of the 2007 crisis.[33] While MFIs and Community Development Banks, such as the Grameen Bank, use innovative lending techniques such as group lending and gradual loans to prevent default, excessive riskiness stemming from off-balance sheet activity, proxied with NII, non-interest income, in this study, must be taken into account as less leveraged MFIs have been found to be more sustainable in the long run, benefiting the individual institution and tax-payers (Hartarska and Nadolnyak, 2007).

While banking has seemingly decreased in the U.S., the off-balance sheet activity of banks, including derivative activities, loan commitments, lines of credit, and credit guarantees, have suggested that banking activity has not diminished but has changed, (Siems and Clark, 2002). Noninterest income[34] doubled from the 70s to the 90s and is heavily influenced by off-balance sheet (OBS), activity. Because OBS activity has proliferated in the U.S., Siems and Clark (2002) state that any efficiency study which does not include this type of activity may not be meaningful, can understate bank output, and bias the empirical estimates between bank size and cost x-inefficiency[35].

Other researchers, (Jagtiani et. al, 1995), have found that off – balance sheet activity, including guarantees[36], foreign currency, and interest rates, had little effect on scale economies

[33] See J. Bradford Delong's Blog (2009)
[34] Noninterest income includes fiduciary activities, service charges on deposit accounts, trading fees, and gains or losses from foreign transactions, trading account gains or losses, fee income (minus service charges on deposits).
[35] When there is x – inefficiency, there is not profit –maximization and cost minimization. It is found in monopolistic market structures and was first introduced by Liebenstein (1966), a Professor at UC Berkeley. It is also defined as the effectiveness with which a given set of inputs is used to produce output. X – inefficiency does not take into account whether or not the inputs are the best ones to be using or if the output is the best to be producing; therefore, it does not look at societal gain from transferring inputs from one production method to another. This phenomena is allocative efficiency which has been found to be small compared to x- inefficiency in the banking literature.
[36] OBS guarantees included the dollar amount of standby letters of credit, commercial letters of credit, and loan commitments. OBS foreign currency included the dollar amount of the foreign currency swap, foreign currency option, and foreign currency futures and forwards. The OBS interest rate included the dollar amount of interest rate swaps, interest rate options, and interest rate future and forward contracts.

and found synergies between foreign currency and guarantees. Casu and Girardone, 2005, concluded that off-balance sheet activity enhanced bank operations in Germany, Italy, and Spain while operation in the UK and France both with and without OBS activity did not statistically differ. Total OBS activities for the U.S. top 20 commercial banks as a percentage of total assets amounted to 1,222 percent as of 2002, although concentrated in the Top 4 investment banks like Japan (Khambata and Bagdi, 2003).

While OBS activity carries substantial risk, U.S. market makers use OBS activity due to low margins from on-balance sheet activity and to reduce market volatility (Khambata and Bagdi, 2003). One of the predominant purposes of this study is to estimate the efficiency of a sample of 32 U.S. Community Development Banks (CDBs). This sample includes all CDBs who in 2008 applied for TARP funds (funds used to buy assets from the troubled large investment banks and the small community banks). The results of **Table 3** on the inefficiency of these banks in June 2006 with NII, non-interest income, show what may be an indicator of the crisis to come. With the macroeconomic depression of 2007, TARP allocations were needed. It is unclear, however, how the TARP distributions were initiated as this study presents a limited analysis with cost only and current profit or profit potential is unclear. However, a few observations can be made.

If you will note, **Appendix A**, shows the list of the Community Development Banks used in the analysis along with their TARP funding and participation in the TLGP as of October 14, 2009. The Shore Bank in Chicago, IL received no TARP money while the International Bank of McAllen was not found on subsidyscope.com. While these banks are the highest cost producers in the sample, they might have the most profit potential and economy of scale. Recently, however, the Shore Bank has considered applying for TARP assistance. The third and fourth

highest cost producing banks, One United Bank of Boston and the First American International Bank of Brooklyn, NY, received $12.1m and $17m respectively. One United Bank of Boston had not paid back its TARP funds as of December 25, 2009,[37] however, it has made its first dividend payment as of February 2009.

The First International Bank of Brooklyn received the largest TARP payment at $17.1 m (less than 0.1% of all bailout funds committed), and has since paid the government $571,389[38]. Larger banks such as Bank of America, Wells Fargo, and Citibank also paid back their TARP funds this month. The First National Bank of Davis Oklahoma was one of the lowest cost operators in the sample and did not receive TARP, as well as the Fort Gibson State Bank of Oklahoma and the Pan American Bank of Chicago, although they are all participating in the TLGP program. The current legislation proposed as of February 3, 2010 is that the Treasury will invest up to $1 billion in small banks and credit unions in the hopes that the 210 eligible CDFIs will maximize their TARP limit and the banks will only have to pay 2% of the Treasury's capital investment after 8 years but will only get TARP if the institution can match private investment with the public investment[39].

This study incorporates NII, non interest income, to proxy for off-balance sheet activity because second bets placed by banks are not easily monitored by off-site call reports, long and short positions are not reported separately, are broadly classified, the riskiness of bank derivative positions can not be evaluated for this reason; not to mention that the derivative positions are not tied directly to the balance sheet. Peek and Rosengren (2005) suggest that bank examinations

[37] "Missed Payment Vexing to Frank," *The Boston Globe*. December 25, 2009 by Todd Wallack. They have a no interest loan which means that they do not have to make-up dividend payments to the government. United Bank is one of the largest black owned internet banks in the country.

[38] http://bailout.propublica.org/entities/172-first-american-international-corp. Copyright ProPublica 2010.
[39] NY Times, February 3, 2010 by Sewell Chan – "Treasury to invest up to $1 billion in Small Banks and Credit Unions"

should be spontaneous so that banks can not "window dress" their derivative positions, which can be easily altered, but that derivatives should be used as they are important instruments to hedge against interest rate and exchange rate risk.[40]

Section 2: The Methodology Section

This study employs the SUR (seemingly unrelated regression) translog cost system (the same approach used in the first two essays) or what has also been termed the traditional non - frontier approach used frequently in the literature[41], where total cost is a function of one or two outputs (loans and NII)[42] and four input prices (price of labor, price of physical capital (this value scales the cost and other input prices to impose linear homogeneity and it is thus dropped in the estimation), price of financial capital, and the price of borrowed funds). It can be written in dual form in a manner similar to Fu and Heffernan (2008):

$$C = f(Y, W) \qquad (1)$$

Where C is total cost, Y is total loans, and W are the input prices described in the Data Section 5. The dual approach implies that cost minimization is achieved when lending is maximized or that while cost is a function of lending, lending is a function of cost.[43] As the first two essays used a

[40] This would mean that bank supervisors would be superior in their trading knowledge over bank traders.
[41] This approach assumes the absence of x-inefficiency, which can stem from non-competitive models where firms can get away with producing at higher cost or from non-optimal inputs or outputs.
[42] A second output includes non-interest income to proxy increases in off-balance sheet activity such as derivatives and asset-backed securities. Advances and Receivables should be included as an output in future studies, especially in light of the 2009 government assistance, TLGP, total liquidity guarantee program, or TARG, troubled asset relief guarantee.
[43] Shephard's Lemma may impose an undesirable assumption that there are no allocative efficiencies. An allocative efficiency can stem from having a highly qualified input to produce an output while society would benefit from a resource allocation of the input to a more skilled means of production (Berger, 1993) [Add to references] Stated by Fu and Heffernan (2008)

similar approach, I will simply refer to the methodology section in those essays for a change of pace.

Efficiency study results are hard to compare as each use various inputs and methodologies, some use the SUR translog methodology, DEA, Fourier flexible frontier, or stochastic frontier approach. This study employs the SUR translog method with 4 inputs (labor, physical capital, financial capital, and borrowed funds) and 1 output (loan volume). Some papers use more involved inputs and outputs, such as Sturm and Williams (2004), who use staff, deposits[44], borrowed funds, equity capital, and interest and non-interest expense as inputs and loans, advances and receivables, off-balance sheet activity, net interest income, and non-interest income as outputs.[45] Das and Das (2007) include the ratio of NPL, non-performing loans, to measure the asset quality, and the ratio of total risk-weighted to total assets to measure risk exposure which were found to increase scale with the Fourier flexible functional form.

Other studies have used DEA analysis, a choice with an advantage in that it does not assume functional form, to find efficiency while also determining the improvement in production of banks with the excess return of the bank's stock, or the stock's return above the risk free rate. Kirkwood and Nahm (2006) are convinced that the excess return is explained by the operational efficiency which is not detected in market movements.

Section 3. A Description on TARP

On October 14, 2008, the U.S. government announced a series of initiatives to strengthen market stability (Federal Reserve Board). The Treasury encouraged federal banks and eligible

[44] Deposits are treated as an input and output, at times. They are an input to loans but an output to depositors as they provide liquidity, security, and sometimes interest (Fu and Heffernan (2008)).
[45] Interest expense is included on interest bearing deposits in the current study. Non-interest expense is not included in the analysis as the amount allocated toward non-interest bearing deposits was uncertain. Advances and receivables were not included and should be included in future studies.

institutions under the thrift regulatory agency to use the Capital Purchase Program and the FDIC's TLGP (Temporary Liquidity Guarantee Program) due to detection of systemic worldwide risk. The fall of Lehman Brothers on September 15, 2008 shocked the world and other investment banks and major market players began to wonder who was next. Details as to why Lehman Brothers was not bailed out like Goldman Sachs, JP Morgan, Citigroup, and the few other megabanks are still unknown[46], perhaps some information needed to be withheld at the time to avoid a total banking collapse in the US and the UK. None the less, these major U.S. Banks, as well as other international investment banks, support microfinance activity and community development initiatives through corporations such as the LISC (the Local Initiatives Support Corporation) which supports non-profits, and liquidity is desperately needed to support small business enterprenuers affected by the credit crunch that seems to have stemmed from too many undiversified contracts or too many bets placed on default (see Dwyer and Tkac, 2009 for the effects of the run on prime money market funds on the commercial paper market).

The largest amount of TARP money went to the institutions determined to be "too big to fail," which simply means that their loss would severely hamper the entire U.S. and the international financial system, affecting confidence, stability, and significant job loss. But allocations were also made to the few community development banks to encourage lending in impoverished areas, see **Appendix A**. The following table shows the TARP funds received by some of the large investment banks as of October 14, 2009 from the Subsidyscope.com website.

[46] See Sorkins book, "Too Big Too Fail," Lehman may not have fallen after all.

Table 3.1

Mega Banks	**TARP Funds as of October 14, 2009**	**TLGP as of 1/31/09**
Citigroup, Inc. – New York	$50 billion	TLGP
Bank of America	$45 billion	TLGP
Goldman Sachs	None	TLGP
JP Morgan	$707.4 m	TLGP
AIG	$69.8 billion	None
Wells Fargo	$25 billion	TLGP

The last page of this study (Appendix A) shows the TARP funds received by the community development banks in this sample and their participation or lack thereof in the TLGP program. The table includes the 32 U.S. CD banks used in the analysis of which 27 are definitely participating in the TLGP program and the range of TARP funding as of October 14, 2009 is anywhere from $0 to $1.7m - $17m. Some of the community development banks opted out of the TARP funding to prevent rules on compensation structures of executives.

Section 4: Data Description

Table 3.2

Variable	Explanation	N	Mean	Std. Dev.	Min	Max
TC	PL*QL + PK*QK + PF*QF + PB*QB	960	7,501,875	10,300,000	1,211,000	53,600,000
PL	Salary & Benefit/Number of Employees	960	32,727	10,639	16,152	66,909
PK	Expense of Fixed Assets/Q of Fixed Assets	960	0.15	0.11	0.03	0.47
PF	Interest Per Deposit/ Interest Bearing Deposits	960	0.01	0.004	0.005	0.02
PB	Expense of Borrowed Money/Q borrowed $*	960	0.02	0.03	0.0007	0.18
Loans	Loans and Leases, net of unearned income	960	244,000,000	307,000,000	33,000,000	1,500,000,000
QL	Number of full time equivalent employees	960	91	90	21	372
QK	Premises and Fixed Assets	960	6,590,563	8,188,437	854,000	43,800,000
QF	Interest Bearing Deposits in Domestic Offices	960	264,000,000	363,000,000	40,000,000	1,740,000,000
QB	Q of other borrowed money**	960	45,500,000	127,000,000	1,186,000	708,000,000

* This value may also include expense on Federal Funds purchased and Securities sold under agreement to repurchase per quantity.
** May also include quantity of federal funds purchased and securities sold under agreements to repurchase.

The data were collected from individual call reports found on the Federal Financial Institutions Examination Council website. A list of the community development banks can be found from the Office of the Comptroller of the Currency. Only CD Banks were examined as the call reports for the community development credit unions were difficult to interpret and lacked similar data as the call reports provided by the community development banks. The analysis was limited to 32 observations out of the 41 banks because the 32 observations had expense on either borrowed money or federal funds purchased and securities sold under agreements to repurchase.

The deposits include transaction and non-transaction accounts. The transaction accounts include NOW, ATS, and telephone and preauthorized transfer amounts. The non-transaction accounts include savings deposits, time deposits of $100,000 or more, and time deposits of less than $100,000. The SUR includes four inputs: the dollar amount of interest-bearing deposits in the domestic offices, the dollar amount of federal funds purchased, securities sold under agreements to repurchase, and other borrowed money (which includes mortgage indebtedness

and obligations under capitalized leases), the number of full-time equivalent employees, and the premises and fixed assets (including capitalized leases). The one output, Loans, is loans and leases, net of unearned income, and the two output model includes Loans and NII, non-interest income, to proxy for off-balance sheet activity.

Table 3.3

June 30, 2006 vs. June 30, 2009
(With and Without NII, Non – Interest Income)

SUR with 1 Output (Loans)	SUR with 2 Outputs (Loans and NII)
June 30, 2009	
Scale (Loan) = 0.9837* N = 960 (32 banks)**	**Scale (Loan and NII) = 0.8432*** N = 1216 (32 banks)**
Cost r- square = 0.9376*	**Cost r-square = 0.9746***
Labor r- square = 0.7887*	**Labor r-square = 0.8288***
Finance r-square = 0.7774*	**Finance r-square = 0.8613***
Borrow r-square = 0.1550*	**Borrow r-square = 0.4237***
June 30, 2006	
Scale (Loan) = 0.9134* N = 870 (29 banks)**	**Scale (Loan and NII) = 0.6714*** N = 1102 (29 Banks)**
Cost r- square = 0.9005*	**Cost r-square = 0.9356***
Labor r- square = 0.3593*	**Labor r-square = 0.3675***
Finance r-square = 0.4457*	**Finance r-square = 0.6224***
Borrow r-square = 0.2316**	**Borrow r-square = 0.3539***

The above table (Table 3) shows that exclusion of nontraditional activities (off-balance sheet activities) leads to misspecification of the banks' output and can lead to incorrect conclusions (Casu and Girardone, 2005). This can be seen in the increase in explanatory power on the cost and input share equations with the addition of NII as an output. Without adding non-interest income (NII), which includes such items as service charges on deposits, income from fiduciary activities, and net gains (losses) on sales of loans and leases, and other real estate

owned, this sample of Community Development Banks looks to be producing efficiently in June 2009 but less efficiently in June 2006, as the left side of the Table demonstrates. The analysis follows Rogers (1998), and Clark and Siems (2002) who both used non-interest income as a proxy for OBS items; this study's findings contrast to Clark and Siems' (2002) scale estimates in that use of NII in their estimates showed more production efficiency in a large bank sample. The off- balance sheet activity, proxied with NII (non-interest income), increases the 2006 and 2009 quarterly cost of this sample of community development banks. The large inefficiency in June 2006 could be an indicator to the crisis that was to come.

While some inefficiency looks to remain in 2009, the important synopsis of the result is that these banks are operating much more efficiently in 2009 than they were in 2006 potentially due to TARP inception but most likely from a cautiousness from the dramatic events beginning early fall 2007, from merger activity with the large investment banks, from a more optimal P/E ratio, and simply from a less uncertain macroeconomic environment. While the inefficiency in 2006 is quite large, it may be a bit overestimated as fees and commissions also come from on-balance sheet activities (Casu and Girardone, 2005). Thus, the efficiency of this sample of banks would appear to lie somewhere in between the scale found without NII, 0.98, and the scale with NII, 0.84, or 0.91. The scale value of 0.84 with Loans and NII as outputs for the 32 U.S. Community Development Banks is comparable to the scale value of MFIs that report to the Mix Market Exchange, specifically the Latin American MFIs. The scale for the entire sample of MFIs with loan and savings volume as the outputs is 0.85 for 1,092 observations, found in the second essay of the dissertation.

The following table shows the annual analysis of the 32 U.S. Community Development Banks from 2008 IV – 2009 III. The results differ from **Table 3** in that **Table 3** is only a cross-

section from the June 30, 2009 and June 30, 2006 call reports and shows the difference in efficiency with use of one output, volume of loans, from the two output model with loan volume and NII, non-interest income. **Table 4** contrasts the results of a one output model using loan volume for annual data from 2008 IV – 2009 III with and without borrowed funds as an input.

Table 3.4

Annual Analysis

SUR Regression on the 32 U.S. Community Development Banks (12/31/08 – 9/30/09)

The results reflect the stability of the banks after the 2007 crisis

3 Input Model	4 Input Model
Cost r-square = 0.9403 Labor r-square = 0.6507 Finance r-square = 0.6839 N = 576 Scale = 0.9725***	Cost r-square = 0.9496 Labor r-square = 0.6824 Finance r-square = 0.6697 Borrow r-square = 0.1724 N = 960[47] Scale = 0.9592***

The 4 Input Model on the right with the expense of federal funds purchased, interest on trading liabilities, and other borrowed money shows the ever so slight reduction in efficiency with the inception of this type of funding.

In comparison, the following table shows the results of the efficiencies of the MIX Market microfinance institutions among various countries studied in the second essay of the dissertation. The U.S. (CD) Community Development banks appear to be more efficient than all of the regional MFIs when off-balance sheet activity is not taken into account, but when it is

[47] There are more observations with this regression to take into account the independent interactions of the price of borrowed funds with the other input prices, its squared term, and its interaction with the output variable.

taken into account the U.S. CD banks resemble the cost efficiency of the Latin American Institutions the most. The Eastern Europe and Central Asian MFIs produce with slight diseconomies of scale while the results indicate that more funds should be directed to Africa, the Middle East, and North Africa.

Table 3.5

Regional Efficiency Outcomes Calculated in the Second Essay

Eastern Europe and Central Asia Cost r-square = 0.9162 Labor r-square = 0.3920 Finance r-square = 0.9264 N = 72 Scale = 1.1692	South Asia Cost r-square = 0.9018 Labor r-square = 0.1732 Finance r-square = 0.9468 N = 79 Scale = 0.7767	East Asia and the Pacific Cost r-square = 0.8905 Labor r-square = 0.4695 Finance r-square = 0.8638 N = 119 Scale = 0.9471
Africa N = 349 Scale = 0.8901	Latin America N = 229 Scale = 0.9111	Middle East and North Africa Insufficient Observations

Section 5: Conclusion and Policy Implications

There are six banking functions according to the Levy Economics Institute of Bard College (Working Paper Number 83): a payment system for check cashing/clearing, and credit and debit cards; secure depositories; financing for housing, consumer debt, and student loans; commercial

banking services for loans, payroll services, and advice; investment banking services for determining the appropriate liability structure of assets; and finally, asset management and advice for households. If at least one of these functions is not being met for low-income, minority, or small entrepreneurial groups, then a community development bank could enter the market and offer these services to the local community. This country has seen historic success of "immigrant banks," which have transformed low-income communities to middle income communities. Community development banks may find that encouraging local deposits just as it encourages local lending and keeping external funding to a minimum, perhaps at 10 %, might prevent unsustainability as brokered money may have contributed to the S & L crisis.

The funding for community development, be it in the form of banks, funds, or corporations will flow as long as the current government supports the revitalization of impoverished communities and employment opportunities for the under-served. An argument can be made for the support of community development banks purely from the TARP assistance, with the highest reported at $17 million for the First American International Bank of Brooklyn, compared to the $50 billion TARP funds for Citigroup and $45 billion for Bank of America, although the large investment banks have quickly and recently paid back these funds.

Community Development Foundations, corporations, and banks help to revitalize communities so that citizens are safe and so that children can participate in healthier activities that foster education, personal relationships, and spirituality. One of the most impacted regions of the LISC initiatives was "Charlotte Street" in the Southern Bronx area of New York. In the 70s, people in this community would set their apartments on fire so that they would be the first on a list for more suitable housing. The LISC used a $10 million grant from the Ford Foundation to buy 2 model homes for this area. These homes were subsidized by the federal government

and had a market value of about $110,000. Today, the market value of the homes is $459,000. Community Development Banks, the LISC, and the Bill and Melinda Gates Foundation, along with Warren Buffet are supporting initiatives to provide more funding to education and invest in human capital to ensure that the United States will not lag behind in innovative research, management, and quantitative expertise as Eastern European and Asian countries have quickly caught up.

Table 3.6: June 30, 2009 Quarterly Regression

	Description	Coefficient	Z-score
PL	Salary Per Employee	0.6423***	5.66
PF	Interest Per Deposit	0.2838**	2.24
PB	Interest Per Q borrowed	0.0739	1.55
PLPL	0.5 * mean/PK scaled	0.2413	1.51
PFPF	0.5 * mean/PK scaled	0.2868*	1.92
PBPB	0.5 * mean/PK scaled	0.0357	0.53
PLPB	0.5 * mean/PK scaled	0.0049	0.04
PFPB	0.5 * mean/PK scaled	-0.0406	-0.30
PLPF	0.5 * mean/PK scaled	-0.2462**	-2.32
Loan	Loans, net of unearned income	**0.9837*** **	17.66
LoanLoan	0.5 * mean scaled	0.1704**	2.32
LoanPL	Mean scaled * Mean and scaled by PK	0.3110***	3.19
LoanPF	Mean scaled * Mean and scaled by PK	-0.2317**	-1.93
LoanPB	Mean scaled * Mean and scaled by PK	-0.0793	0.32
Constant		-0.0261	-0.34
LaborShare			
PL	Salary Per Employee	0.3935***	5.82
PF	Interest Per Deposit	-0.4985***	-8.54
PB	Interest Per Q borrowed	-0.0699**	-1.98
Loan	Loans, net of unearned income	-0.0706*	-1.67
Constant		-0.1508***	-3.54
FinanceShare			
PL	Salary Per Employee	-0.4985***	-8.54
PF	Interest Per Deposit	0.6573***	10.18
PB	Interest Per Q borrowed	0.0189	0.49
Loan	Loans, net of unearned income	0.1051**	2.23
Constant		0.0382	0.80
BorrowShare			
PL	Salary Per Employee	-0.0699**	-1.98
PF	Interest Per Deposit	0.0189	0.49
PB	Interest Per Q borrowed	0.3144	1.61
Loan	Loans, net of unearned income	0.2985	1.24
Constant		-0.4995**	-2.05
N		**960**	32 banks
Cost r-square	Explanatory power of Cost Eq.	0.9376	
Labor r-square	Explanatory power of Labor Share Eq.	0.7887	
Finance r-square	Explanatory power of Finance Share Eq.	0.7774	
Borrow r-square	Explanatory power of Borrow Share Eq.	0.1550	

References

Balkenhol, B., 2008. Microfinance and Public Policy: Outreach Performance and Efficiency. Houndsmill, England.

Barth, James R.,Caprio, Gerard, and Levine, Ross. "Bank Regulation and Supervision: What Works Best?," *Journal of Financial Intermediation*, April 2004.

Barth, James R., Caprio, Gerard, and Levine, Ross. "Rethinking Bank Regulation: Till Angels Govern," Cambridge University Press, 2006.

Battese, G.E., Coelli, T.J., 1995. A model of technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20(2), 325-32.

Bernanke, Ben; Pinsky, Mark; et. al., "The Economic Crisis and Community Development Finance: An Industry Assessment." June 2009 Working Paper 2009 – 05. Federal Reserve Bank of San Francisco.

Berger, A.N., 2007. International comparisons of banking efficiency. Financial Markets, Institutions & Instruments, 16(3), 119-144.

Berger, A.N., Mester, L.J., 1997. Inside the black box: What explains differences in the efficiencies of financial institutions. Journal of Banking and Finance 21, 895-947.

Berger, A.N., Mester, L.J., 2003. Explaining the dramatic changes in performance of U.S. banks: Technical change, deregulation, and dynamic changes in competition. Journal of Financial Intermediation 12, 57-95.

Battese, G.E., Coelli, T.J., 1995. A model of technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20(2), 325-32.

Board of Governors of the Federal Reserve System (as of November 11, 2009) http://www.federalreserve.gov/bankinforeg/tarpinfo.htm.

Bos, J.W.B., Kool, C.J.M., 2006. Bank efficiency: The role of bank strategy and the local markets conditions. Journal of Banking and Finance 30, 1953-1974.

Casu, Barbara and Girardone, Claudia (2005) "An analysis of the Relevance of Off-balance Sheet Items in Explaining Productivity Change in European Banking." *Applied Financial Economics*, **15**, 1053 – 1061.

Caudill, S., Gropper, D., Hartarska V., 2009. Which microfinance institutions are becoming more cost-effective with time? Evidence from a mixture model. Journal of Money, Credit, and Banking 41(4), 651-672.

Clark, Jeffrey A. and Siems, Thomas F. (November 2002) "X-Efficiency in Banking: Looking Beyond the Balance Sheet," *Journal of Money, Credit, and Banking*, Vol. 34,

No. 4 http://muse.jhu.edu

Cull, R., Demirguc¸-Kunt, A, Morduch J., forthcoming. Does regulatory supervision curtail microfinance profitability and outreach? World Development.

Cull, R., Demirguc-Kunt, A, Morduch J., 2007. Financial performance and outreach a global analysis of leading MFIs. The Economic Journal 117, F107-F133.

Daley-Harris, S., 2009. State of the Microcredit Summit Campaign Report 2009. MicrocreditSummit. Washington D.C.

Das, A., Das, S., 2007. Scale economies, cost complementaries, and technical progress in Indian banking: Evidence from Fourier flexible functional form. Applied Economics 39, 565-580.

Dooley, Michael and Hutchison, Michael. "Transmission of the U.S. Subprime crisis to emerging markets: Evidence on the decoupling-recoupling hypothesis. *Journal of International Money and Finance,* Volume 28, Issue 8, December 2009, Pages 1331 – 1349.

Dymski, Gary Arthur (2009) "Financing Community Development in the U.S.: A Comparison of "War on Poverty" and 1990s – Era Policy Approaches. *Rev Black Polit Econ* (Springerlink.com)

Dwyer, Gerald P. and Tkac, Paula. "The financial crisis of 2008 in fixed-income markets." *Journal of International Money and Finance*, Volume 28, Issue 8, December 2009, Pages 1293 – 1316.

Ellinger, Paul. "Specification of Inefficiency in Banking: A Comparison of Cost and Profit Function Approaches." 1997

Fries, S., Taci, A., 2005. Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. Journal of Banking and Finance 29, 55-81.

Fu, Xiaoqing (Maggie) and Heffernan, Shelagh (2008) "Economies of Scale and Scope in China's Banking Sector," *Applied Financial Economics*, **18**, 345 -356.

Gonzalez, A., Rosenberg, R., 2006. The state of microfinance—Outreach, profitability, and poverty: Findings from a database of 2,300 microfinance institutions. Available at SSRN: http://ssrn.com/abstract=1400253.

Gropper, Daniel M. (1991) An Empirical Investigation of Changes in Scale Economies for the Commercial Banking Firm, 1979 – 1986, *Journal of Money, Credit, and Banking,* Vol. 23, No.4

Gutierrez-Nieto, B., Serrano-Cinca, C., Mar, M., 2007. Microfinance institutions and efficiency. Omega: The International Journal of Management Science 35, 131-142.

Hartarska V., Mersland, R., forthcoming. What governance mechanisms promote efficiency in reaching poor clients? Evidence from rated MFIs. European Financial Management.

Hartarska, V., Caudill, S., Gropper, D., 2007. Productivity of microfinance institutions in Eastern Europe and Central and Eastern Asia. Working paper available at ssrn.com.

Hermes, N., Lensink, B.W., Meesters A., forthcoming. Efficiency and outreach of microfinance institutions, World Development; also available at ssrn.com.

Hughes, J, Mester, L., 2008. Efficiency in banking: Theory practice and evidence. Working paper 08-1, Federal Reserve Bank of Philadelphia.

Jagtiani, Julapa; Nathan, Alli; Sick, Gordon (1995) "Scale Economies and Cost Complementarities in Commercial Banks: On – and Off – Balance Sheet Activities," *Journal of Banking and Finance, **19***, 1175 -1189.

Karnani, Aneel (2007) "Microfinance Misses Its Mark" *Stanford Social Innovation* review, http://www.ssireview.org/articles/entry/microfinance_misses_its_mark/

Kim, Youn-suk and Koo, Hyeng Keun. "Asia's contagious financial crisis and its impact on Korea." *Journal of Asian Economics,* Volume 10, Issue 1, Spring 1999, Pages 111 – 121.

Kirkwood, Joshua and Nahm, Daehoon (2006) "Australian Banking Efficiency and Its Relation to Stock Returns" *The Economic Record,* Vol. 82, No. 258, September, 2006, 253-267.

Kneiding, Christoph and Tracey, Paul (2009) "Towards a Performance Measurement Framework for Community Development Finance Institutions in the UK" *Journal of Business Ethics*. Kneiding works at the CGAP division of the World Bank and Tracey works at the University of Cambridge, UK.

Lensink, Robert, Meesters, Aljar, and Naaborg, Ilko (2008) "Bank efficiency and foreign ownership: Do Good Institutions Matter?," *Journal of Banking and Finance* **32** (2008) 834 – 844.

Leon, J., 2009. Cost efficiency frontier: An empirical analysis of Peruvian municipal banks. Canadian Journal of Development Studies 29(1–2), 161–182.

LISC website: "The greatest real estate turnaround ever," CNNMoney.com by Les Christie on November 25, 2009.

Mersland, R., 2009. The cost of ownership in microfinance organizations. World Development 37, 469-478.

Mersland, R., Strøm, R.Ø., 2008. Performance and trade-offs in microfinance organizations—Does ownership matter? Journal of International Development 20, 598-612.

Mersland, R., Strøm, R.Ø., 2009. Performance and governance in microfinance institutions. Journal of Banking and Finance 33, 662-669.

Mersland, R., Strøm, R.Ø., forthcoming. Microfinance mission drift? World Development.

Minsky, Hyman P. Papadimitriou, Dimitri B., Phillips, Ronnie, J. and Wray, L. Randall (1992) 'Community Development Banks,' Working Paper No. 83. *Jerome Levy Economics Institute.*

Morduch, J., 1999. The microfinance promise. Journal of Economic Perspectives 37, 1569-1614.

Nawaz, A., 2009. Efficiency and productivity of microfinance: Incorporating the role of subsidies. Working paper, University of Gottingen, Germany.

Nasiripour, Shahien. "Derivatives: Bailed – Out Banks Still Making Billions Off Risky Bets," Huffington Post (September 29, 2009)

Papadimitriou, Dimitri B., Phillips, Ronnie J., and Wray, Randall L. (May 1993) "The Community Reinvestment Act, Lending Discrimination, and The Role of Community Development Banks," Working Paper No. 95. *The Jerome Levy Economics Institute*.

Paxton, J., 2007. Technical efficiency in a semi-formal financial sector: The case of Mexico. Oxford Bulletin of Economics and Statistics 69(1), 8305-9049.

Peek, Joe and Rosengren, Eric S. (1997) "Derivatives Activity at Troubled Banks," *Journal of Financial Services Research.*

Randolph, Allyson B. Cascade – A Community Development Publication of the Federal

Reserve Bank of Philadelphia Winter 1999. "New Report Spotlights Growing CDFI Strength, Effectiveness"

Rauch, James H. and Hendrickson, Jill M. (2004) "Does Bank Consolidation Hurt the Small Business Borrower?" *Small Business Economics.*

Reille, X., Foster, S., 2008. Foreign capital investment in microfinance. Focus note. CGAP, Washington D.C.

Stiroh, K., 1999. Measuring input substitution in thrifts: Morishima, Allen-Uzawa, and Cross-Price Elasticities. Journal of Economics and Business 51, 145-157.

Sturm, J. and Williams, B. (2004), "Foreign bank entry, deregulation and bank efficiency: Lessons from the Australian Experience," *Journal of Banking and Finance,* **28**, 1775 – 99.

Swanson, B., 2008. The role of international capital markets in microfinance, in: Sundaresan, S., (Ed.), Microfinance: Emerging Trends and Challenges. Cheltenham, UK; Northampton, USA.

Tadesse, S., 2006. Consolidation, scale economies, and technological change in Japanese banking. International Financial Markets, Institutions, and Money 16, 425-445.

Van Cayseele, Patrick; Wuyts, C., 2007. Cost efficiency in the European securities settlement and depository industry. Journal of Banking and Finance, 31(10), 3058-79.

Varian, H., 1984. The nonparametric approach to production analysis. Econometrica 52(3), 579-597.

Yaron, Jabob. 1992a "Successful Rural Finance Institutions", Discussion Paper No. 150, Washington, D.C.: World Bank, 1992a.

Zacharias, J., 2008. An investigation of economies of scale in microfinance institutions. http://w4.stern.nyu.edu/glucksman/docs/Zacharias2008.pdf.

Appendix 1. The Countries and Observations Per Country in the Sample (N = 1,254)

Used in the First Essay

Country	Observations Per Country
Albania	12
Argentina	5
Armenia	12
Azerbaijan	22
Bangladesh	6
Benin	23
Bolivia	59
Bosnia & Herzegovina	41
Brazil	47
Bulgaria	9
Burkino Faso	10
Cambodia	28
Cameroon	14
Chad	3
Chile	8
China	4
Colombia	24
Croatia	4
Dominican Republic	16
East Timor	2
Ecuador	57
Egypt	17
El Salvador	14
Ethiopia	45

The Gambia	4
Georgia	18
Ghana	10
Guatemala	19
Guinea	3
Haiti	3
Honduras	29
India	88
Indonesia	5
Jordan	10
Kazakhstan	12
Kenya	38
Kosovo	9
Kyrgyzstan	12
Madagascar	4
Malawi	4
Mali	4
Mexico	64
Moldova	8
Mongolia	7
Montenegro	15
Morocco	20
Mozambique	3
Nepal	14
Nicaragua	36
Nigeria	12
Pakistan	1

Paraguay	5
Peru	106
Philippines	16
Romania	3
Russia	58
Rwanda	2
Senegal	19
Serbia & Montenegro	4
South Africa	12
Sri Lanka	1
Tajikistan	18
Tanzania	16
Togo	3
Trinidad & Tobago	3
Tunisia	4
Uganda	42
Vietnam	4
Zambia	4
Total	**1,254**

Appendix 2: TARP Fund Distribution for the 32 U.S. Community Development Bank

Community Development Bank	TARP Funds as of October 14, 2009	TLGP as of 1/31/09
Albina Community Bank – Portland, OR	None	TLGP
American Metro Bank – Chicago, IL	None	TLGP
Central Bank of Kansas City – Kansas City, MS	None	TLGP
City National Bank of New Jersey	Not found on Subsidyscope.com	Not found on Subsidyscope.com
Franklin National Bank of Minneapolis	$11.9 million	TLGP
Guaranty Bank and Trust Company – Belzoni, MS	$14 million	TLGP
Legacy Bank – Milwaukee, WI	$5.5 million	None
Mission Valley Bank – Sun Valley, CA	$5.5 million	TLGP
Pacific Global Bank – Chicago, IL	$3 million	TLGP
North Milwaukee State Bank – Milwaukee, WI	None	TLGP
Pan American Bank – Chicago, IL	None	TLGP
Southern Bancorp Bank of Arkansas	$11 million	TLGP
Citizens Trust Bank – Atlanta, GA	$7.5 million	TLGP
City First Bank of D.C., N.A. – Washington, D.C.	None	TLGP
Community Bank of the Bay – Oakland, CA	$1.7 m	TLGP
Community Commerce Bank – Claremont, CA	Not found on Subsidyscope.com	Not found on Subsidyscope.com
First American International Bank – Brooklyn, NY	$17 m	TLGP
First National Bank of Davis, OK	None	TLGP
Fort Gibson State Bank – Fort Gibson, OK	None	TLGP
Harbor Bank of Maryland – Baltimore, MD	$6.8 m	None
Highland Community Bank – Chicago, IL	None	TLGP
Industrial Bank – Washington, D.C.	$6 m	None
International Bank – McAllen, TX	Not found on Subsidyscope.com	TLGP
Liberty Bank and Trust of New Orleans, LA	$5.6 m	None
Mission Community Bank – San Luis Obispo, CA	None	TLGP
N.Y. National Bank – Bronx, NY	Not found on Subsidyscope.com	Not found on Subsidyscope.com
OneUnited Bank- Boston, M.A.	$12.1 m	TLGP
Premier Bank – Wilmette, I.L.	Not found on Subsidyscope.com	Not found on Subsidyscope.com
Seaway Bank and Trust Company – Chicago, I.L.	None	TLGP
Shorebank – Chicago, I.L.	None	TLGP
Southern Bancorp Bank – Ruleville, MS	$11m	TLGP
Tri-State Bank of Memphis	$2.8m	TLGP