

Determining Optimal Capital Allocation to Microfinance Institutions

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Undergraduate College

Leonard N. Stern School of Business

New York University

May 2008

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Abstract

Microfinance has become an important and effective tool for helping fight poverty by encouraging entrepreneurship and providing funding to individuals who have no access to traditional sources of capital. Because of its social impact, high returns, and significant diversification benefits, the microfinance sector has received increasing attention from mainstream investors and capital markets. With many different vehicles for investment, large amounts of capital are being fed into the industry, especially into the debt and equity of microfinance institutions. While this is very helpful in scaling up the industry to help as many people as possible, the capital may not be allocated as efficiently as possible. Most funds that invest in microfinance institutions focus their funding on the top-tier institutions. This paper looks to see whether individual institutions are able to absorb all of this capital by testing for a statistically significant negative relationship between the amount of capital an institution has and its return on assets. My empirical tests show that there is a statistically significant relationship and a point at which a MFI cannot absorb more capital efficiently. This suggests that funds may be better off investing in a diverse array of MFIs instead of concentrating investment in the top-tier. This paper also looks at what other factors significantly affect the returns of a microfinance institution. The hope is that understanding which factors are most important will help funds looking to diversify away from the potentially overcrowded top-tier MFIs understand where to best invest their money.

Motivation

Microfinance, the business of making small loans to low-income individuals, has garnered a lot of interest as it is a successful tool for helping to alleviate poverty. In 2006, Muhammad Yunus and the Grameen Bank received the Nobel Peace Prize for their work to develop microfinance into a well-accepted global industry and aiding millions of people in rising from poverty.¹ Originally, microfinance mostly came from not-for-profit or government subsidized entities, but it has emerged as a profitable industry and has received much attention for its combination of social impact and high returns.

This rise in interest can be seen through the surge in investment from multiple sources including mainstream institutional investors. Investors look to make socially responsible investments but are also drawn to the industry's high potential returns related to low loan losses and the high interest rates often charged by microfinance institutions (MFIs). In addition, investors seek the unique portfolio diversification microfinance investment can provide. Recent research by Nicolas Krauss and Ingo Walter has shown that because of low correlation to market cycles, microfinance could potentially offer significant diversification benefits and reduce portfolio volatility. Their research shows that microfinance has no statistically significant correlation to global capital markets (represented by various broad indices) and could therefore be a source of diversification for international investors.²

Microfinance investment can take many forms. There is traditional direct investment in the debt and equity of MFIs, often used by niche, microfinance oriented

¹ Associated Press, "Microcredit Pioneers are Awarded Nobel." *International Herald Tribune*. October 12, 2006.

² Krauss, Nicolas and Walter, Ingo. "Can Microfinance Reduce Portfolio Volatility?" February, 2008.

funds. Recently, however, different types of structured finance vehicles for investment by more mainstream investors have been created such as Collateralized Debt Obligations (CDOs) and direct securitization of microfinance loans. The most prominent example of a Microfinance CDO is BOLD 2006-1 (Blue Orchard Loans for Development), which offered five-year fixed-rate funding to 21 MFIs. The CDO used five different currencies in order to be accessible to mainstream investors and convenient for MFIs. The first direct securitization deal in Microfinance was developed by BRAC in 2006. This deal was innovative because it bypassed MFIs by deriving payables directly from the end-borrowers' loan repayments.³

Data on securitized portfolios is not readily available since it is a very recent development. This paper focuses on investments in MFIs. The goal is to find out whether MFIs are limited in the amount of capital they can absorb efficiently, and if so, to predict in what range that may be. Through the study, I use MFI data to determine the effect of the size of the gross loan portfolio (GLP) and total assets (TA) on the returns of an MFI. I also test other important MFI traits to determine their effects (if any) on returns.

The economic logic motivating this study is based on the economic principle of diminishing returns. Marginal returns on capital will naturally diminish as a given borrower deploys more capital. Having access to more capital comes with the double-edged-sword of knowing how to use that capital efficiently. My hypothesis for this study is that MFIs could have trouble absorbing the large amounts of capital that will flow to them as more mainstream investors and capital markets become involved, especially

³ "Microfinance Cracking the Capital Markets II." *Acción Insight*. Vol. 22, May 2007.

since microfinance is a relatively young industry. The capital would therefore not be used efficiently and returns would diminish accordingly. The goal of this analysis is to determine whether empirical data on MFIs consistently show a significant trend of diminishing returns, and to try and predict at what point marginal returns equal zero.

The practical motivation for this paper is to help MFIs and funds investing in MFIs understand how to allocate the recent and growing influx of capital efficiently. Because of diminishing returns, any given MFI can only absorb a certain amount of capital efficiently regardless of its specific traits. According to Acción, microfinance investment vehicles (MIVs) and funds allocate their investment to the top 50 “tier 1” MFIs.⁴ This suggests that the capital coming from mainstream investors is focused highly unevenly among a select few MFIs. The results of this study suggest that it may actually be better to spread lending into lower-tier MFIs than flood the top-tier MFIs with capital.

Understanding how to optimally allocate microfinance capital should also help the social goals of microfinance. Efficient use of capital by MFIs implies that the institutions only give out loans to the most deserving borrowers. Promoting these borrowers will help their personal welfare and help to develop the economy in which they are located.

Methodology

The theoretical model motivating these tests was adapted from a classic cross-border capital transfer model developed by G.D.A. MacDougall.⁵ This model, based on

⁴ “Microfinance Cracking the Capital Markets II.” *Acción Insight*. Vol. 22, May 2007.

⁵ MacDougall, G.D.A. “The Benefits and Costs of Private Investment from Abroad: A Theoretical Approach.” *Economic Record*, March 1960.

the principle of diminishing returns, determines the absorptive capacity of a country as the capital stock at the point at which a country's marginal product of capital (MPK) equals zero. I adapt this model to determine the absorptive capacity of a given MFI. I use the MFI's gross loan portfolio or total assets as its capital stock and attempt to derive an MPK curve using a regression model. As marginal product of capital is the derivative of the firm's output function, I first derive a firm's output function using a multi-variable regression model and then take the partial derivative with respect to either GLP or TA of the regression equation to find an equation for MPK. Setting the resulting MPK equation equal to zero provided values for the implied absorptive capacity of an MFI.

The regression models use an MFI's return on assets (ROA) as the response variable and various forms of the MFI's Gross Loan Portfolio or Total Assets as the predictor variables. I used the natural log of either GLP or TA ($\ln(\text{GLP})$ or $\ln(\text{TA})$) in most regressions in order to rationalize the data. In order to test for diminishing returns, I used various polynomial regressions that could, if statistically significant, produce production functions with downward sloping derivatives. In general, regressions with the predictor variable and the square of the predictor (quadratic) were the most statistically significant:

$$ROA = \beta_1 + \beta_2 * \ln(GLP) + \beta_3 * \ln(GLP)^2 + \varepsilon$$

In this example, GLP was the predictor variable, but a similar equation applies for TA.

This study uses regressions focusing on GLP and regressions focusing on TA as the response variables. The regressions focusing on GLP were intended to isolate the portion of an MFI's assets dedicated to microfinance. The implicit assumption in these regressions is that all capital from a microfinance fund invested in an MFI is allocated to

the loan portfolio. The regressions then help to determine the absorptive capacity of MFI's gross loan portfolio. The regressions focused on TA are based on the hypothesis that as an MFI receives capital above its absorptive capacity, those funds may not go into the loan portfolio and may be inefficiently used elsewhere.

Several other variables that could explain the response variable (ROA) are also used in multi-variable regressions. The goal is to isolate the effect of GLP or TA on ROA by determining whether those predictors remain significant when other explanatory variables are included. In addition, testing these variables can help a potential investor understand which MFI-specific factors affect returns and should be considered when making investment decisions.

I use various methods to test the significance of these variables and to understand what combination of variables produce the most significant regression:

- Regressing each variable against ROA individually in order to see its statistical significance and to what degree it explains ROA
- Running a regression using all the variables in order to see which variables are significant and the coefficients predicted by the test
- Testing variables in various combinations with the GLP and TA predictors in order to find the most significant variables and the best regression
- Performing a best-subsets regression with all the variables holding $\ln(\text{GLP})$ and $\ln(\text{GLP})^2$ (or $\ln(\text{TA})$ and $\ln(\text{TA})^2$) constant

In order to determine which regression is "best" using the best-subsets regression, I look both at the adjusted R^2 and the Mallows C_p statistic. I look for the combination

of a high R^2 and a Mallows C_p that comes closest to the number of predictor variables based on a common rule of thumb to test for the best combination of predictor variables.⁶

Data

All data for this study are taken from the MIX Market, an online database with financial, performance, and outreach data on over 1000 MFIs.⁷ The MIX Market rates the level of disclosure by an MFI using a diamond system. One diamond signifies the lowest level of disclosure and five the highest. A five diamond rating requires outreach data, financial data, audited financial statements and adjusted data such as due diligence.⁸ For this study I use only five-diamond-rated MFIs in order to limit the analysis to data with the highest integrity and guarantee consistency across the dataset.

The exclusive use of five-diamond data may bias the results of this study. Because of the disclosure requirements, the data may exclude younger MFIs or those without the flexibility to have their financial statements audited. The data therefore are most likely biased toward the higher tiers of MFIs in terms of size, prominence, and performance. This bias may actually help to prove the hypothesis of the study that, regardless of best practices a given MFI can only absorb a limited amount of capital. If this trend is evidenced in the five-diamond MFIs, it could be extrapolated that lower tiered MFIs would face similar effects. The bias may, however, negatively affect the goal of the study to understand what non-capital related variables help determine MFI

⁶ Thank you to Professor William Greene, NYU Stern School of Business Department of Economics, for explanation of the use of Mallows C_p .

⁷ "Microfinance: The MIX Market Home Page." *Microfinance Information Exchange*. Accessed May, 2008. http://www.mixmarket.org/en/home_page.asp

⁸ "Diamond System." *Microfinance Information Exchange*. Accessed May, 2008. <http://www.mixmarket.org/en/diamond.system.asp>

returns. Ideally, funds looking to diversify their funding to lower-tiered MFIs could use these data to understand what MFI specific factors are most important. However, these factors may differ in significance for lower-diamond MFIs.

The five-diamond data include 250 MFIs, each with at least two years of data from 1998 to 2006. Using each year as a separate data point yield 1,464 unique data points. Each data point includes MFI performance (ROA) and size (GLP and TA). In addition, each data point includes various MFI specific factors. These factors encompass financial data (Total Equity, Average Loan Balance/Borrower), performance metrics (Operational Self Sufficiency, Portfolio at Risk > 30 days), outreach indicators (Percent of Borrowers that are Women, Borrowers/Staff), and dummy variables to indicate the type of MFI. A full list of variables used and their descriptions can be found in Exhibit A.

A summary of the distributions of the variables is in Exhibit B. I do not use variables with less than 1000 observations in the regressions in order to guarantee the robustness of the data. Of note are the range of MFI size (from \$29 thousand to \$421 million in total assets and \$4 thousand to \$345 million in gross loan portfolio) and the mean (\$20.6 million total assets, \$15.3 million gross loan portfolio) and median (\$5.5 million total assets, \$4.0 million gross loan portfolio). The large difference between the mean and the median suggests that a few very large MFIs skew the mean upward.

Another potential issue with the data is that all monetary values are not adjusted for inflation. Inflation should not be a major problem because of the relatively short time frame involved in the study, but may affect comparisons between years. Using “year” as an explanatory variable, however, in statistical tests does not show up as statistically

significant with either a 95% or 90% confidence level in most regressions, suggesting that inflation does not significantly affect the data.

In addition, all available data from MIX are converted to US\$ using an exchange rate applied at the end of each year. Currency translation is an unavoidable risk when comparing data from several different countries. The fact that all financial statements given are audited should help to mitigate this risk somewhat.

Statistical Tests

Determining Absorptive Capacity

A summary of the results of the statistical tests can be seen in Exhibit C. The main predictor factors of $\ln(\text{GLP})$ or $\ln(\text{TA})$ and $\ln(\text{GLP})^2$ or $\ln(\text{TA})^2$ are consistently highly statistically significant. In addition, $\ln(\text{GLP})$ and $\ln(\text{TA})$ always have a positive coefficient and $\ln(\text{GLP})^2$ and $\ln(\text{TA})^2$ always show a negative coefficient, suggesting strong evidence of the hypothesized diminishing returns to MFIs. R^2 s for the best regressions are in the mid to high 60%s, suggesting satisfactory explanation of ROA by the predictors involved.

The tests all allow for the prediction of the absorptive capacity of an MFI by setting the partial derivative of GLP or TA equal to zero. The different tests produce a wide variety of results. The predicted gross loan portfolio capacity ranges from \$25 thousand to \$648 million with an average of \$30 million (Exhibit D). The extremes of this range do not make very much intuitive sense. The \$30 million average seems more intuitive as the current mean gross loan portfolio is around \$15 million. This suggests that MFIs can absorb more capital into their loan portfolios but only up to a certain point.

The best GLP regression, however, by the Mallows Cp test and adjusted R² comparison, only implies a maximum gross loan portfolio of \$3.8 million (Exhibit C). This is not particularly intuitive either, and therefore it may make more sense to look at the tests using ln(TA).

Tests using ln(TA) may be more applicable to understanding the absorptive capacity of MFIs because they can take into account funds received by MFIs that are not allocated to their primary activities, microfinance loans. Once again, all tests had ln(TA) highly statistically significant and positive and ln(TA)² highly statistically significant and negative. The best adjusted R² from these tests was 68.7%, slightly better than the 66.7% from the ln(GLP) tests. The best regression's implied absorptive capacity suggests a given MFI can efficiently absorb capital up to \$36 million in Total Assets (Exhibit C). This does make intuitive sense given the mean of \$20 million and median of \$5 million in Total Assets for the MFIs tested. There are still several MFIs out there that can efficiently absorb more capital but there are some that have crossed this theoretical limit.

While there will be variation in absorptive capacity from one MFI to another, this test is designed to isolate total assets as much as possible by including other available explanatory factors. As ln(TA), ln(TA)², ln(GLP), and ln(GLP)² remain highly significant when other explanatory variables were included, it would seem that the diminishing returns argument is valid even while allowing MFI specific variables to be taken into account. A regression using all available explanatory variables has a slightly lower adjusted R² than the "best" regression (67.8% vs 68.7%) but implies a higher maximum value for total assets (\$47 million vs \$36 million) (Exhibit C).

Understanding Important MFI Specific Factors

In order to determine the significance of other explanatory factors I use three different methods:

1. Regress each variable independently against ROA
2. Regress all variables against ROA
3. Determine which variables were significant in the “best” regressions

The results of each method can be found in **EXHIBIT C**. Many variables are significant in some tests and not in others while others were significant in all tests:

- All tests: Total Assets, Total Equity, Borrowers/Staff, Operational Self Sufficiency, Cost/Borrower
- Alone only: Year, Number of Borrowers, Write off Ratio
- Alone and TA tests: GLP/TA
- All regressions except alone: ALB/Borrower, ALB/GNI, % Women Borrowers
- Most regressions: Portfolio at Risk > 30, Operating Expense/LP

Variables that show significance across all tests clearly are important factors in determining MFI returns. However, total assets and total equity, while significant, showed a coefficient of effectively zero suggesting that though important, they do not significantly affect the returns of an MFI. This may be the result of the size of these variables, which typically tend to be in the millions, versus ROA, which is a percentage. Operational self-sufficiency consistently shows strong significance and a relatively high positive coefficient, implying that the ability of an MFI to cover its operating costs through revenue is very important in determining its returns. This suggests that an MFI

that keeps costs low relative to revenues will have higher returns. However, cost per borrower shows surprisingly positive coefficients and borrowers per staff shows negative coefficients. Perhaps this means that MFIs that spend more resources on helping their borrowers achieve better returns and that the costs that should really be reduced are more related to overhead and loan loss provisions.

Variables that only show significance alone are probably not as important. The low confidence of their significance in regressions with other variables suggests that other variables serve to explain MFI returns much better. However, it is interesting to look at the coefficients of these variables. The write-off ratio consistently shows a negative coefficient, which makes intuitive sense given that an MFI does not want to write off its loans. Number of borrowers has a zero or slightly negative coefficient, implying that MFIs currently probably lend to an appropriate number of borrowers.

I drew importance to the variable GLP/TA, which shows high significance alone and in both $\ln(\text{TA})$ regressions because it helps to illustrate one of the hypotheses of this test. The hypothesis that tests involving $\ln(\text{TA})$ would be more important than those involving $\ln(\text{GLP})$ is based on the belief that an MFI with excess capital may not apply that capital to its main line of business, its loan portfolio. The significance of GLP/TA helps to prove this hypothesis because of its positive coefficient, which implies that MFIs that use more of their capital toward their loan portfolio achieve better returns.

The variables that are not significant alone but are highly significant when added to other regressions are likely to represent important factors in determining MFI returns. The percent of borrowers that are women is often cited as an important criterion for investment in MFIs because women are perceived to be more responsible with the

funding than men. This appears to be a valid assumption as the percent of women borrowers is both highly significant and positive. The significance of ALB/Borrower is interesting because its slightly negative coefficient suggests that MFIs that grant smaller loans have better returns. ALB/GNI shows a similar negative trend implying that it is better to give smaller loans in poorer countries. This has important echoes of the idea of absorptive capacity. If an MFIs clients are unable to absorb more capital (higher loan balances), then the MFI itself will be at a certain point unable to absorb more capital.

As Portfolio at Risk > 30 days and Operating Expense/LP shows significance in most regressions, they are likely also important factors. Both of their coefficients negative and therefore intuitively make sense.

Noting Insignificant Factors

It is also important to understand which factors consistently show an insignificant statistical relationship with ROA throughout the tests of this study. Most surprisingly, the dummy variables for type of MFI were generally insignificant. My initial hypothesis regarding these variables was that non-profit institutions would show lower returns than the other for-profit types of institutions. Non-profits, focusing on the social goals of microfinance, often offer subsidized loans and outreach programs that I would expect to drive down profits and returns. However, the non-profit dummy never shows statistical significance and in fact has a positive coefficient in most tests.

The only type dummy variable that shows significance at a 95% confidence level was the dummy for MFIs that fall under the category of “bank.” The positive coefficient

suggests that banks may be better suited to handle microfinance than other types such as co-ops, credit unions, and non-bank financial institutions.

Another factor that shows up as consistently insignificant is the amount of savings in the MFI. This factor also has implications about the type of MFI. MFIs that hold deposits are more likely to be banks. However, whether or not an MFI takes deposits does not seem to affect returns as the relationship is insignificant and coefficient always essentially zero.

Conclusions

As microfinance gains popularity among mainstream investors, it is important to avoid speculative investing and the creation of bubbles by understanding how to optimally allocate capital to the institutions that lend to the ultimate borrowers. Efficient capital allocation should not only help investors, but should help borrowers as well by enforcing market discipline. The results of this study therefore have practical implications, especially for principals and fiduciaries looking to invest in MFIs.

A paper by Tilman Ehrbeck suggests that active, venture capital-type investment in microfinance is becoming a best practice. It is important to fully understand the capital needs of an MFI based on its history, lifecycle, team, goals, and specific traits and then take an active role in oversight.⁹ The empirical results of my study can help such investors understand what traits of an MFI are important to focus on when doing due diligence.

⁹ Ehrbeck, Tilman. "Optimizing Capital Supply in Support of Microfinance Industry Growth" (Working Paper.) *Microfinance Investor Roundtable*, October, 2006.

Most importantly, it would seem that concentrating funding on the top 50 MFIs or even only on the top tier MFIs will eventually lead to misallocation of capital and lower fund returns. When determining which MFIs to lend to, a fund can look at various factors to make sure the MFI will be able to use that capital efficiently. It can look first at the size of the MFI and make sure that it makes sense to provide it with capital given the predicted capacity of around \$36 million in total assets. While this factor should only be used as a rough guide it can help investors understand the capital needs of an MFI—does the MFI need more capital and if so how much can it handle?

A fund also has the ability to do more due diligence into the MFI's use of capital. It should look at what other funding the MFI is receiving and what it has done with the money. This can help a fund to see if an MFI has been receiving too much funding—as the more popular MFIs may be—and whether the MFI is using the capital in a way that will generate the best returns. In this case it may help to look at the Gross Loan Portfolio as a percentage of Total Assets to understand how much of this capital is actually being committed to microfinance.

In conducting due diligence there are some factors that deserve more attention than others. One of the most important is the ability of the MFI to cover its operating costs through revenues. In this sense it may be better to fund an MFI with consistent revenues and low costs. Cost, however, is tricky because while it is better to have lower operating costs as a percentage of the loan portfolio, it may pay the MFI to spend resources on each borrower in order to assist them. MFIs that lend to more women also deserve more interest. It would seem that the responsibility with money often attributed to women in the developing world does in fact impact returns.

Interestingly, the type of MFI does not seem to have much bearing on returns. Therefore a fund should not exclude MFIs from its investment decision simply because they are non-profit. The fact that these institutions are more socially oriented does not seem to affect their returns in the way other factors do. Perhaps government or other subsidies to help the organization balance the effects of offering lower-interest rates or other programs to borrowers.

Further Research

Because of data constraints, I am unable to conduct corollary studies that would help to understand absorptive capacity and investment in microfinance better. When that data does become available, it will be interesting to see what new light it sheds on the topic. It would be interesting to study the effects of the sources of capital on its returns. This would help see whether certain institutions are inflating certain MFIs because of connections or reputation and how this type investment affects returns.

In general it would be interesting to look at this topic from the supply side. The MIX Market currently has limited data on microfinance investment funds, but will likely have more robust data in the future. When such data becomes available, it would be helpful to analyze where the funds are investing and the associated returns.

It would also be interesting to analyze the effects and returns associated with the new microfinance investment vehicles such as the CDOs and securitized products. It remains to be seen whether investment that bypasses MFIs avoids some of the capital problems that those institutions face. As these types of products are new and not yet as prevalent as MFIs, such analysis will have to wait until a time when enough data is available for an empirical study. In the meantime, qualitative studies can likely be done

looking at specific investment vehicles, their investments, and their successes and failures.

It is an exciting time to get into microfinance, but all investment should be done with care. As most microfinance investment is currently done through MFIs, it is important to understand what factors determine their performance. As the industry grows and attracts more capital it will become increasingly important to select investments wisely.

EXHIBIT A: Variable Reference Chart

Name	Abbreviation	Explanation
Gross Loan Portfolio	GLP	Gross Loan Portfolio of MFI
Year	Year	Year of data point
GLP/TA	GLP/TA	(Gross Loan Portfolio)/(Total Assets)
Total Assets	TA	Total Assets of MFI
Total Equity	TE	Total Equity of MFI
Savings	S	Savings
ALB/Borrower	ALB	Average Loan Balance per Borrower
ALB/GNI	ALB/GNI	(Average Loan Balance per borrower)/(Country's per capita Gross National Income)
Borrowers/Staff	B/S	(Number of Borrowers)/(Number of Staff Members)
Op Self Sufficiency	OpSS	(Financial Revenue) / (Financial Expense + Loan Loss Provision Expense + Operating Expense)
# of Borrowers	B	Number of Active Borrowers
Portfolio at Risk >30	PAR	(Portfolio at Risk for over 30 days)/(Gross Loan Portfolio)
% Women Borrower	W	Percent of Borrowers that are Women
Op Expense/LP	Op/LP	(Operating Expense)/(Period Average Gross Loan Portfolio)
Non Profit?	NP	Dummy Variable for whether the MFI is a Non Profit
Bank?	Bank	Dummy Variable for whether the MFI is a Bank
Co-op/CU?	CU	Dummy Variable for whether the MFI is a Co-op or a Credit Union
Non Bank FI?	NBFI	Dummy Variable for whether the MFI is a Non Bank Financial Institution
Cost/ Borrower	Cost/B	(Operating Expense)/(Period Average Number of Active Borrowers)
Write off Ratio	WR	(Write offs for 12 month Period)/(Period Average Gross Loan Portfolio)

EXHIBIT B: Data Summary

Indicator	# Obs	Median ('000s)	Mean ('000s)	SD ('000s)	Min ('000s)	Max ('000s)
Gross Loan Portfolio	1,463	\$4,086,058	\$15,355,578	\$32,856,600	\$4,705	\$345,920,510
Total Assets	1,460	\$5,596,741	\$20,606,939	\$43,802,644	\$29,148	\$421,065,823
ROA	1,222	3.36%	2.71%	9.45%	-110.91%	51.93%
GLP TA	1,460	78.45%	75.19%	16.33%	2.06%	140.08%
Average Loan Balance Borrower	1,425	\$433	\$739	\$895	\$9	\$10,172
Average Savings Balance Saver	443	\$197	\$1,439	\$7,842	\$0	\$132,090
ALB per capita GNI	1,367	43.68%	70.50%	96.02%	1.65%	913.36%
ASB per capita GNI	440	27.31%	132.00%	571.69%	0.00%	7462.72%
Borrowers Staff	1,372	122	141	91	4	807
Bottom Half below PL	156	9.00%	22.99%	29.51%	0.00%	100.00%
Clients Below Poverty Line	195	60.00%	51.34%	37.85%	0.00%	100.00%
Clients earning <\$1	177	19.00%	33.17%	38.24%	0.00%	100.00%
Write off Ratio	1,130	0.66%	1.57%	2.81%	-0.84%	38.29%
Women Borrowers	1,267	63.00%	64.96%	27.17%	0.00%	100.00%
Total Equity	1,456	\$2,179,586	\$5,075,529	\$9,698,608	-\$1,664,459	\$154,901,889
Savings	1,382	\$0	\$7,001,938	\$24,815,701	\$0	\$256,915,556
Savers Staff	1,279	0	61	140	0	851
ROE	1,220	11.31%	10.18%	131.32%	-3829.45%	1698.52%
Profit Margin	1,387	13.47%	-4.74%	107.05%	-1478.09%	100.00%
Portfolio at Risk>30	1,317	2.22%	4.06%	6.57%	0.00%	81.37%
Operational Self Sufficiency	1,386	115.56%	116.82%	37.34%	6.34%	337.65%
Operating Expense LP	1,222	21.24%	28.27%	24.46%	0.00%	443.02%
Number of Savers	1,297	0	17,594	59,689	0	1,014,474
Number of Active Borrowers	1,425	11,133	32,619	72,982	19	972,212
Loans below 300	463	55.00%	52.27%	36.83%	0.00%	100.00%
Cost Borrower	1,192	\$100	\$135	\$128	\$0	\$949

EXHIBIT C: Regression Results

Variables	Alone	ln(GLP)^2 Regressions		ln(TA)^2 Regressions	
		All	Best	All	Best
ln(GLP)	.0196**	.13389**	.193**	(.04320)**	(.03831)*
ln(GLP)^2	-	(.006607)**	(.00636)**	-	-
ln(TA)	0.0175**	.06684	-	0.33424**	.33071**
ln(TA)^2	-	-	-	(.009458)**	(.009500)**
Year	0.00736**	(.0000205)	-	0.0001716	-
GLP/TA	0.171**	.12862	0.0067	.08829**	.06987**
TA	0.00000**	.00000000**	0	.00000000**	.00000000**
TE	0.00000**	.00000000**	0	.00000000**	(.00000000)**
Savings	0.00000	(.00000000)	0	(.00000000)	(.00000000)**
ALB/Borrower	0.000002	(.00002159)**	(0.000019)**	(.00002376)**	(.00001835)**
ALB/GNI	0.00148	(.008087)**	(0.00818)**	(.007955)**	(.008255)**
Borrowers/Staff	0.000153**	(.00006339)**	(0.00006)**	(.00007261)**	(.00006417)**
Op Self Sufficiency	0.219**	.202554**	0.211**	.201807**	.207856**
# of Borrower	0.00000**	(.00000005)	-	(0.00000007)	-
Portfolio at Risk >30	(-0.319)**	(.06584)	(0.0808)**	(.07205)*	(.08753)**
% Women Borrower	(0.0147)	.032421**	0.0288**	.028548**	.027056**
Op Expense/LP	(0.173)**	(.07891)	(0.0654)**	(.08719)**	(.07979)**
Non Profit?	(0.00268)	.00355	-	.00529	.004465
Bank?	0.0165*	.01079	-	.01234	.012884**
Co-op/CU?	(0.0033)	(.00191)	-	.00154	-
Non Bank FI?	(0.0014)	(.00170)	0.0692*	.00052	-
Cost/ Borrower	(0.000058)**	.00015581**	0.000153**	.00015549**	.00013882**
Write off Ratio	(0.529)**	(.09458)	-	(.11615)	-
F		90.46	136.42	93.95	126.26
Adjusted R^2		66.9%	67.6%	67.8%	68.7%
Implied GLP or TA Capacity		\$25,146	\$3,886,253	\$47,190,238	\$36,244,184

* = Significance at 90% confidence level

** = Significance at 95% confidence level

EXHIBIT D: Results and Interpretations Summary [GLP]

Result	Mean	Standard Deviation	Minimum	Maximum
Coefficient ln(GLP)	0.167415333	0.241802894	-0.463	0.79
Coefficient ln(GLP)^2	-0.010059548	0.010742078	-0.0424	-0.000329
Implied GLP	\$30,788,932	\$107,809,946	\$25,146	\$648,945,130

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Acknowledgements

NYU Stern School of Business: For supporting the Stern Honors program.

Professor Marti Subrahmanyam: For organizing the program and his insightful points into the topic and for helping me meet my advisor, Professor Walter.

Professor Ingo Walter: For his deep knowledge of the subject matter and his advice, insight, and guidance throughout the whole thesis process despite being on sabbatical.

Professor William Greene: For insight into the use of Mallows Cp, one of the most important facets of my regression analysis.