

# **RAISING THE BAR**

## **ACHIEVING SCALE AND SUSTAINABILITY IN MICROLENDING IN THE UNITED STATES**

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## I. INTRODUCTION

Small business development is an important component of many community development efforts. This should come as no surprise: small business account for 99% of all employers and two-thirds of all new net jobs; small business is the engine that brings economic prosperity to communities (U.S. SBA, 2000). Recognizing the importance of small business building strong local economies, Community Development Financial Institutions (CDFIs) have long dedicated much of their financing to small businesses.

These CDFIs are social innovators, applying private sector banking practices to small businesses that are not served by conventional financing sources. Since the late 1970's Community Development Financial Institutions have provided financing to small business as one of their tools for combating poverty and economic distress in low-wealth areas. Individual CDFIs choose to provide small business finance for unique reasons dependent on their mission and community development strategy. Some choose it as a means of providing employment in areas of high unemployment. Others use it to support their urban revitalization efforts by recruiting businesses and services to distressed urban areas. Those CDFIs that focus their attention groups that are left out of mainstream economic activity (ethnic minorities, low-income persons, women) employ small business finance as a means of building wealth and business skills among these target groups.

Financing small businesses directly impacts communities by creating jobs and additional income, but these programs also achieve powerful effects beyond these obvious benefits. Financing a low-income entrepreneur's business often builds the family's net worth, providing a springboard for the family to buy a home, educate their children and or re-invest in the community. The increased presence of small businesses can help spur additional private and public reinvestment in distressed areas. Also, small business owners are often the source of leadership in a community; financing minority, women and low-income entrepreneurs often creates leaders from among underrepresented segments of society.

For these and other reasons, many CDFIs have chosen to offer small business financing programs to accomplish their mission. The number of CDFIs involved in small business finance has increased steadily since the 1970's. In the first several years CDFIs were making only several hundred small business loans a year. By 2000 these figures had increased dramatically, as reported in a survey of 379 CDFIs (which includes most of the larger CDFIs involved in small business lending). In this year these CDFIs originated more than 14,000 small business loans and managed \$600 million in loans (CVFI Data Project, 2001).

This study focuses on the small business lending experience of Self-Help, a CDFI located in North Carolina. Self-Help operates a broad variety of community development lending and investment programs aimed at providing economic opportunity to low-wealth communities and people. With more than \$1 billion in assets, it is one of the two largest CDFIs in the United States. It began its commercial and small business lending in 1984 and has provided more \$227 million to 2,600 businesses in North Carolina.

Today the CDFI industry and Self-Help is facing a critical moment in its small business lending programs. Bank competition in small business lending has increased significantly over the last 5 years as banks have applied new technologies, specifically credit scoring, to small business lending. Existing CDFIs are finding it more difficult to expand their programs to achieve the advantages of scale. In addition, most CDFIs are not able to provide small business finance in a manner that is financially sustainable to their organizations, making growth even more difficult and the long-term viability of the program indefinite.

This report investigates some of the newest small business lending practices used by banks that might have application to the CDFI industry. In as much as CDFIs have a history of bringing the best banking practices to the practice of community development finance, it is not unreasonable to believe that these new small business lending practices might be useful to CDFIs. In particular, the use of credit scoring small business loans by banks could be a powerful tool to help CDFIs overcome some of the barriers they are now facing in providing these loans. This report reviews current banking credit scoring usage and then tests the practicality of applying this technique to Self-Help's small business portfolio. Using a database of small business loans originated by Self-Help over the last decade, the feasibility of using credit scoring for selecting loan applications is tested. Based on these tests, recommendations are made for the possible application of these tools at Self-Help. Finally, suggestions for further research are presented aimed at building a more sophisticated scoring model for the CDFI industry.

## **II. A REVOLUTION IN SMALL BUSINESS LENDING**

Until the 1990's, banks processed small business loans in much the same way they processed larger corporate loans. Financial and credit information was collected about a company, its principals, the market and industry trends. Face-to-face meetings were normally required to gain in-depth knowledge of a business's operations and plans and to assess the "character" of the business owner/manager. An experienced loan officer (or underwriter, depending on the size of the loan) analyzed this information and a decision was made based on the judgment of experienced staff. This method is time-consuming and costly, so banks did not use this process for most small business loan applicants through this process. Instead smaller loan requests from businesses were generally underwritten as consumer loans, a process that involves much less time and cost for the bank but does not serve the customer as well.

Beginning in the early 1990s several commercial banks, Wells Fargo among them, began adapting the credit scoring technologies that had been used in the consumer lending field to small business loans (Financial Institution Consulting, Inc. 2001). Credit scoring is the process of assigning a single quantitative measure, or score, to a potential borrower that reflects the borrower's relative chance of going into delinquency or default (Feldman, 1997). These scores have been used since the 1980s in the underwriting of credit card, auto and mortgage loans. The application of credit scoring has permitted banks to process consumer debt much more efficiently while increasing the availability and decreasing the cost of credit for consumers.

### **Credit Scoring Models**

Small business lending was thought to require too much individualized and non-standard information to fit into a quantitative scoring model. In the late 1980s credit analysts at Fair Isaac & Co. Inc. determined that the personal credit history of small business owners is highly predictive of loan repayment, especially for loans under \$100,000 (Mester, 1997). Indeed, the willingness and ability of business owners to pay personal credit appears to extend to be closely related to their ability to repay business credit. Early credit scoring models were developed by outside vendors, such as Fair Isaac. Fair Isaac was one of the earliest vendors of business credit scoring systems and remains the industry leader, although many of the larger banks have begun to develop their own customized scoring systems. Credit scoring models are proprietary, owned by vendors or banks, thus there is not a lot of information available about the exact composition of the scores.

All credit scoring models use a statistical analysis of historical data on loan performance to determine which borrower characteristics are useful in predicting whether a loan performs well. Analysts begin with 50 or 60 factors about borrowers and, using regression analysis, narrow these to 8 or so factors that are most predictive of loan performance. All business credit scoring models are based on personal and business credit factors: whether they pay their loans on time; the presence of bankruptcies, collections and liens against the business or individual; and the balances remaining on current credit accounts. Some models are augmented with other factors such as the value of equity in homes and investment accounts, the type, age and size of the business, and debt coverage ratios (Mester, 1997).

Most of this information needed for a credit score is drawn from third-party sources such as Dun and Bradstreet, Experian and personal credit reports. Since much of this information is not available for very small businesses, these credit scoring models are not particularly useful for very loans to very small businesses (Yan, 2000). Remarkably, most credit scores models do not usually include business financial information. In fact, Fair Isaac's most popular small business scoring system does not require the firm to provide financial statements (Feldman, 1997).

More recently a few efforts have been made to refine the basic architecture of the business credit score. Research by Yan (2000) suggests that adding firm-specific data on years in business, the number of trade credits open in the last 12 months and the amount of revolving credit open would help increase these models predictive power.

Along similar lines, in 1995 Robert Morris Associates, in partnership with Fair Isaac, created a model (SBSS 5.0) that adds company financial factors to the model. This model was developed from data derived from 17 different banks, so could be used by most banks in the U.S. Financial ratios were found to be very weak predictors of loan performance when view abstractly, but when compared to industry norms (using RMA's Annual Statement Studies) these ratios enhanced the model's performance (Bishop, 2002). Originally the SBSS 5.0 model also segments loans by size of loan but that was later dropped because it wasn't considered a significant factor. This model is now recommended for all small business requests up to \$250,000.

Most banks use scoring models provided by specialized vendors. Fair Isaac is still the dominant player in the field, but there are now at least ten other vendors competing in this space. Larger banks have the option of developing their own models. The biggest advantage of using an off-the-shelf model is lower cost: low-cost models developed by Fair Isaac cost in the \$10,000 to \$30,000 range. Customized models require very large portfolios to create; one company estimates that a minimum of 75,000 records is required to develop a statistically valid system. The minimum cost of a customized package is likely to cost more than \$80,000. Then there is the cost of maintenance. Models must be constantly refined to adapt to changing business environments and customer bases. Wells Fargo alters its own proprietary model about every 18 months (Prager, 1999). Vendors provide updates to their products routinely, but banks that use in-house systems must develop their own maintenance schedule to constantly test and redefine their models (Cleaver, 2002).

### **Credit Scoring Usage Proliferates**

By the late 1990's credit scoring was widely adapted by banks. In 1997, the Federal Reserve's *Loan Officer Opinion Survey on Bank Lending Practices* gave evidence that scoring small business loans became common practice among banks. In this survey 38 of the 54 banks responding indicated that they used credit scoring models. Larger banks (those with assets of greater than \$15 billion) used credit scoring more often than smaller banks (Federal Reserve Board, 1997). Fair Isaac reported in 1997 that 250 banks used its small business scoring system, and 25 of the top 30 banks with the largest small business portfolios used credit scoring. Also, by 1995 many of the largest small business lenders (Wells Fargo, Bank of America, Citibank) had developed their own in-house credit scoring systems (Feldman, 1997). By 1999 credit

scoring dominated small business lending. That year, the Federal Reserve Bank of San Francisco polled banks in their district about the use of credit scoring in small business lending and found that 90% of small business loans were originated by banks using credit scoring (Palmer, 1999).

Another indication of how prevalent credit scoring has become is the application of the technique to larger loans. Originally thought to be only useful for loans under \$100,000, now most banks use it for loans up to \$250,000. A 1998 survey by the *American Banker* found that the median size of scored loans had increased from \$100,000 in 1997 to \$150,000 in 1998 (*American Banker*, 1998).

### **Using Credit Scoring Systems**

Contrary to common thought, banks do not use credit scores to auto-approve all loans under maximum loan amount. As Ron Feldman, Senior Financial Analyst at the Minneapolis Fed point out, “Credit scoring systems...are not like HAL, the all controlling computer from *2001: A Space Odyssey*. Most importantly, the systems do not independently approve or reject a loan application.” (Feldman, 1997).

Lenders use credit scores in many different ways, ranging from simply adding the score as another piece of data in their judgment-based underwriting, to approving and rejecting all loans above and below certain numeric scores. Smaller and community banks, where personal relationships are crucial to attracting and retaining customers, tend to use score to streamline their human reviews. Larger banks most often use score to automatically approve loans with score above a certain “safe” level, and reject loans below a score that has proven to lead to very high defaults. Loans in the middle range are given human reviews. In addition, most lenders allow for “overrides” – pulling out loans that are automatically approved or rejected for a closer human review because of important additional information that is not taken into consideration by the score or a lack of data to provide an accurate score.

(Chart: bell curve before and after credit scoring from Aspen manual)

### **The Impact Of Credit Scoring**

Credit scoring has revolutionized small business lending by simplifying loan underwriting. This one innovation has led to a variety of breakthroughs in this banking niche:

- **Simpler Applications for Borrowers:** The reduction of underwriting to a small number of quantitative factors has streamlined the documentation required for borrowers. Many credit scoring systems initially require only a one-page application from the applicant. Most credit scoring systems can accept applications over the web as well, providing further convenience for some applicants.
- **Quicker Reviews:** Loans that are auto-approved can be approved in less than a day, sometimes in a matter of hours. Pacific National Bank reduced its approval time from two days to four hours when it switched to credit scoring (Eljas, 2001).

- **Pre-Approved Credit:** By identifying a few crucial quantifiable underwriting criteria, credit scoring has radically transformed loan marketing. Now banks, using third party data sources, can identify potential customers that would qualify for loans before those businesses even apply for credit. Businesses are then contacted by mail with offers of pre-approved credit. Using this technique banks can target their marketing to business that will be approved for credit, often doubling loan approval rates.
- **Cost Savings for Banks:** Simplified application procedures and marketing techniques have drastically reduced the cost of small business lending. The marketing and origination costs associated with small business loans has always hampered banks from making small loans to businesses, and the reason why many businesses had to use consumer credit to finance their companies. *It is estimated that credit scoring reduces the cost of lending by 75%, from an average of 4% of a loan amount to 1%* (Tansey, SBA, 2002).
- **Expansion of Geography:** Since marketing and loan applications are no longer limited by geography, credit scoring has permitted lenders to extend credit to small businesses located in areas without bank branches. Mailings of pre-approved applications and web-based application procedures have allowed some of the major credit scorers, such as Wells Fargo, to establish a nation-wide market.
- **Reduction in Credit Losses:** Credit scoring has led, in some cases, to lower loan losses because they are now able to assess risk more accurately. In addition, underwriters are freed to concentrate their attention to those loans that require closer review. Fair, Isaac reports that banks that adopt credit scoring models experience an immediate 20% reduction in loan losses (Cleaver, 2002).
- **Individualized Risk-Based Pricing:** Most banks typically “smooth” interest rates, averaging rates between the higher risk and lower risk customers because of the difficulties of accurately assessing the risk of individual credits. Credit scoring has permitted banks to calibrate loan pricing relative to projected losses on a loan-by-loan basis. This has allowed banks to widen their lending pool to riskier loans and accept higher losses, compensating with higher interest rates. For example, Wells Fargo varies its credit scored loans from prime plus 1% to prime plus 8.75% for loans that are expected to have loss rates from 0.5% to 8% (Prager, 1999).
- **Increase in Volume:** There are signs that banks using credit scoring may have an advantage in this market. This could be due to more customer-friendly features (quicker approvals and simpler application procedures), expansion of markets beyond physical branches, and the ability to increase market share by lending down-market. Federal Reserve Banks in Kansas City and San Francisco report that banks using credit scoring are showing exceptional gains in their small business lending (Feldman, 1997). A study of 200 largest banks in 1997 found that banks using credit scoring showed an average 8.4% increase in portfolio share of small business loans, or \$4 billion per institution (Foster, 2001). Bank of America found it could lower the passing score for small

business application because of the use of credit scoring, resulting in 10% more loan approvals (Prager, 1999).

The combined impact of these innovations has revolutionized small business lending, increasing the convenience for borrowers, reducing costs and expanding markets for banks. Wells Fargo provides the starkest example of how credit scoring revolutionized small business lending. In one year after it launched its direct mail, pre-approved business credit product, it jumped from the 11<sup>th</sup> largest to the 2<sup>nd</sup> largest small business lender in the U.S.

The advantages of credit scoring might well be adopted by CDFIs. However, while CDFIs are interested in cost efficiencies and better customer service, they are also interested in the effect banking innovations have on low-income communities and low-wealth borrowers. How does credit scoring affect the delivery of small business credit to these community development markets?

### **Scoring's Effect on Low-Income Communities**

In as much as credit scoring is a relatively new practice and community development is not banks' first priority, there have been few studies of the impact of scoring on fair lending practices. Research on mortgage lending discrimination has shown that after controlling for all risk factors, minority borrowers continue to have a harder time obtaining conventional mortgages than whites (Carr and Megbolugbe, 1993), despite the use of credit scoring. Business credit scoring models could be biased because of their reliance on data from consumer credit reports. Because these reports are based on borrowing practices more common in white and middle-class neighborhoods (e.g. standard credit card and mortgage loans) they may accurately reflect racial or income biases. Many sub-prime lenders and other consumer finance sources often used by minority borrowers do not report to credit bureaus, and some of these lenders only report negative credit records. This practice could possibly hide discriminatory lending patterns. Even Eugene Ludwig, the Comptroller of the Currency warned in 1997 that credit scoring systems have sometimes led to discriminatory results due to biases imbedded in scoring models and the misuse of "overrides." (Green, 2000). For these reasons, there is considerable skepticism as to whether business credit scoring can in fact be free from racial or other biases.

In 1999, the Atlanta Federal Reserve Bank studied the effect of bank credit scoring in low and moderate-income (LMI) communities in metropolitan areas in six southeastern states. This study found that credit scoring had significantly positive effects on the amount of small business credit provided to low-income communities, and a mixed effect on moderate-income communities (Padhi, 1999). In another study two years later, Frame, Padhi and Woosley analyzed bank microlending in all census tracts in these same six southeastern states. In this study they found that credit scoring highly correlated with increased lending in low- and moderate income census tracts, and estimated credit scoring increased lending by an average of \$16.4 million per census tract. It also found that credit scoring increases the likelihood that large banks will make small loans in LMI census tracts (Frame, 2001).

There has yet to be any research conducted on scoring's impact on lending to minority- and women-owned firms. It appears that credit scoring in itself is not a major source of lending discrimination. Yet because of the uncertainty remaining, users of credit scoring models must be

away of the potential disparate impact these model might have on minority and low-income borrowers.

Credit scoring has made radical changes in the delivery, availability and economics of small business loans. Yet it is too early to make definitive conclusions about the efficacy of this credit model. Extensive performance records are not yet available. Credit scoring models developed during economic expansion of the 1990s have not yet been through a full economic cycle. Analysts are waiting to see how these models hold up through the current recession.

Yet the advantages credit scoring has reaped for the banking industry and it's small business customers are too good to ignore. There could be great promise for CDFIs in these techniques. The advantages are too attractive to entirely dismiss as inappropriate for use by CDFIs in their small business lending. CDFIs must look to this critically at this tool to determine what components are beneficial to their work and how those components can be applied to their specialized lending markets.

### **III. APPLICATION OF CREDIT SCORING TO SELF-HELP'S SMALL BUSINESS LENDING**

Given the fact that credit scoring has improved small business access to bank loans, why not try to apply these techniques to CDFI small business lending? It appears that many of the advantages gained by banks by using scoring could help solve some of the problems of cost, customer convenience and scale. Since Self-Help is one of the CDFI industries largest and oldest small business lenders and the author has worked there for 17 years, it seemed natural to try to apply these techniques to Self-Help's practices.

Self-Help's first loans were small term loans made to small businesses, loans today that would be called microcredit but at the time no such term existed. Over the years Self-Help expanded its range of small business loan products to include lines of credit, construction and renovation loans and permanent mortgages. The maximum loan size increased as Self-Help asset base grew. Today, Self-Help makes loans as small as \$500 and as large as \$5 million. However, the vast majority of business loans made by Self-Help remain fairly small due to Self-Help's focus on assisting low-wealth entrepreneurs.

#### **Small Business Loan Database**

To test the use of credit scoring techniques at Self-Help, a database of small business loans and loan factors was created. Although Self-Help has very complex loan databases of payment histories and loan impact information on current and past borrowers, the factors used to underwrite and approve loans are not held in electronic form. A database of underwriting factors was created by extracting key factors from paper loan approval documents that are preserved for all approved business loans at Self-Help. These factors were added to basic loan data already held in various databases (e.g. loan number, loan amount, date loan was originated) to create the database used in this study.

Not all 2,100 business loans were included in the database. Several whole classes of loans were removed from consideration. The largest class of removed loans is "partnership" loans made by Self-Help over the last 17 years. Partnership loans are originated by Self-Help and are assets of Self-Help, but are approved by other development organizations. These partnerships are arrangements of convenience – other organizations that provide small business training or other community development services often outsource their lending programs rather than develop that capability. Self-Help, as North Carolina's leading CDFI, is a natural partner to contract with for loan administration services. In most of these partnerships Self-Help originates and services the loans but does not market, take applications or approve the loans. Because Self-Help does not approve the loans it has no underwriting information on the borrowers and therefore over 600 loans from five partnerships are not included in the database.

Loans made before 1990 and after July 1999 were not included either. The earlier loans were left off the database because these loans did not include as much underwriting information in the loan files as later loans. A smattering of loans before 1990 were included that did have better underwriting data, but for the most part insufficient underwriting information these loans made the process of extracting data from loan files unrewarding. Loans originated after July, 1999 were excluded to insure that all loans had at least three years of payment histories. The goal of

credit scoring is to be able to predict the payment performance of a loan, thus sufficient payment histories are necessary to determine loan performance.

Lastly, loans were selected by size. Literature on credit scoring by banks indicates that it has been most successful in loans under \$100,000 because of similarities with consumer lending at that amount. Self-Help also used consumer-oriented underwriting factors in its small loans. Assessments of larger loans are based more on business credit issues. The \$100,000 level was chosen as the cut-off because all decisions on loan under this amount are greatly influenced by personal credit histories. Loans over \$100,000 are not included in the database but there is no minimum size (the smallest loan in the database is \$300.00).

In the end, the database consisted of 750 small business loans representing almost all small business loans of \$100,000 or less that were underwritten and approved by Self-Help between January 1, 1990 and July 31, 1999.

### **Self-Help's Loan Approval Methodology**

Before describing the data collected for these 750 loans, it is useful to understand the current method of approving loans at Self-Help. Like almost all CDFIs engaged in small business lending, Self-Help essentially applies a process that is very similar to the process used by banks for their corporate loans. Detailed information is gathered from small businesses including historical personal and business financial statements, business and personal tax, financial projections, business and personal credit histories, details on the business operations and sometimes formal business plans. Lending staff meets with the principals of the business in order to obtain a sense of their capabilities and character. At times lending staff also talks to customers and vendors to better understand the firms' abilities. Financial data is analyzed against industry norms and historical trends. All this information is synthesized into a narrative credit memo or loan transmittal that summarizes the strengths and weaknesses of the company and makes a loan recommendation. The decision process is based on the judgment of underwriters - those personnel with experience in assessing loan applications and observing the performance of approved loans - in consultation with the loan officer.

This process is time-consuming but provides a fairly complex understanding of a business. CDFIs' processes may differ somewhat from banks' because of the lack of readily available borrower information. Many small businesses applying for loans from CDFIs do not have complete financial, credit or other business information. CDFIs may often try to compensate for the lack of business-related information by gaining insights from visits to the business location and conversations with vendors and customers. Most often CDFIs must simply make educated guesses about these missing factors or simply reject a loan application if too much crucial information is lacking.

Self-Help's current method for approving loans follows these procedures. Smaller loans applications (those under \$25,000) generally don't require quite as much information and decisions are made based on a more superficial analysis than for larger loans. In most cases, a less complex analysis is appropriate for smaller loans because the business are less complex and there is simply less information to assess.

### **Database Fields: Data Collected for Each Loan**

Key factors used to make loan decisions were extracted from narrative loan transmittals. However this extraction was not as simple as one might think. Not all factors are expressed in quantitative form; surrogate measures were developed for most of these factors. Because of incomplete information, there is not a consistent set of approval factors for all loans. Instead, one generally finds 5-8 factors used for any single loan decision, but not necessarily the same 5-8 criteria for all loans in the database. Thus there are a large number of blanks in the database - fields in which data is not available data for a specific loan. However, over the entire 750-loan database there is a significant number of loans with similar factors. Lastly, much of the quantitative data found in the loan transmittals (e.g. debt coverage ratios, personal debt-to-income ratios) may not be completely accuracy. In many cases quantitative factors were derived from incomplete or inaccurate financial reports submitted by the applicants. At this point in time, 5-10 years after the data was submitted, it is impossible to verify the accuracy of any one loan's information. Thus some of the factors contain may contain "dirty" data which inevitably clouds any statistical analysis. Despite these limitations, this database is first of its kind in the CDFI industry and is large enough from which to derive some useful statistical correlations.

The database is composed of five major clusters of decision criteria in addition to loan performance data. Each of these factors can be used as a variable in a statistical analysis that correlates underwriting factors to loan performance. These factors are described in detail in Appendix A, and are summarized here:

#### Loan Decision Variables (32 variables):

- Management Capacity
- Business Financial Condition
- Personal Financial Condition
- Personal Credit History
- Collateral/Co-Borrower Factors

#### Loan Performance Factors (5 variables):

- Loan Delinquency Data
- Loan Loss data

#### Loan Descriptors (6 variables):

- Loan number
- Original and outstanding Loan Amount
- Date of Loan Origination

#### Demographic Variables (5 variables):

- Race and gender of primary borrowers
- Household income of primary borrowers
- Year business started

Altogether there are potentially 48 pieces of data, or fields, for each of the 750 loans.

### **Assessment: Description of Loans**

This database represents a very accurate historical picture of Self-Help's business lending practices. As the chart below illustrates, this group of loans is heavily populated with small loans and loans made to minority and women entrepreneurs, Self-Help's primary targets.

Microloans (loans of \$35,000 or less) compose 85% of the total database. This is no surprise since Self-Help started making very small loans and expanded its presence in this market niche as it built branch offices throughout North Carolina and participated in federal programs supporting microlenders. Loans to businesses owned by ethnic minorities make up 48% of the total and women entrepreneurs received 50% of the total. Loans to rural businesses, the third major target of Self-Help’s lending, accounted for 41% of the sample. These percentages are very close to the total figures for similarly sized loans at Self-Help, therefore this sample of Self-Help loans is a good representation of Self-Help’s entire small business loan portfolio.

**TABLE 1 - SMALL BUSINESS LOAN DATABASE SUMMARY**

	Number	Percent
Minority-Owned Businesses	338	47%
Race not known	32	4%
Woman-Owned Businesses	373	50%
Gender not known	7	1%
Rural Businesses	301	41%
Location known	15	2%
Size of Loan		
\$0 to \$5,000	264	35%
\$5,001 to \$15,000	212	28%
\$15,001 to 35,000	151	20%
\$35,001 to \$100,000	123	17%

Because the focus of the analysis is to determine if key underwriting variables are statistically correlated to loan repayment, the loan decision variables and loan performance are particularly important. There are 32 loan decision variables providing data on the major decision criteria used by Self-Help. The shortcoming of this dataset is the lack of complete data for each loan. In most fields, data is available for most every loan. However there are some key loan decision variables in which the number of observations is low. Data was least available for these variables:

- Business profitability (available for 324)
- Business net worth (available for 343 loans)
- Education factors (available for 383 loans)
- Debt coverage (available for 446 loans)
- Beacon score (available for 479 loans)

Unfortunately, several of these variables (beacon score and education) are particularly important to the loan decision methodology, so the lack of data limits the actual useful size of the database. A complete description of the observation frequency is presented in Appendix B.

The presence of a large number of delinquent loans is important to make statistic inferences about loan performance, and this database contains a large number of non-performing loans. And fortunately, payment data is available on every loan. The chart illustrates the prevalence of

loans that were delinquent at anytime during their term: almost half (47%) of the 750 loans in the database had at one time made a late payment (late at least 30 days, or one month). Surprisingly, 24% of the loans had been 120 days late at least once. A significant number has also been charged off - 11 %. In general, Self-Help’s small business customers are not like those of banks, in which the vast majority are current on all loan payments. At Self-Help, almost half of all loans were delinquent at one point in their payment histories, and one quarter of all loans have been 4 payments late. This points to a portfolio in which many customers will have delinquency problems some time or another, making it a more difficult and costly portfolio to manage than typical bank portfolios.

**TABLE 2 - LOAN PERFORMANCE**

	Number	Percent
30 days delinquent or more	320	43%
60 days delinquent or more	245	33%
90 days delinquent or more	201	27%
120 days delinquent or more	183	24%
Never delinquent	397	53%
Loans charged off	81	11%
Performing loans	391	52%
Non-performing loans	119	18%

The purpose of a credit scoring system is to quickly select loans that should be approved or denied. Thus this analysis employs two definitions of loan performance: one for loans that should be approved under any circumstances (“performing loans”) and another for loans that perform so poorly that Self-Help should always deny (“non-performing loans”). A separate statistical analysis is used to solve for performing loans and non-performing loans. Definitions of a “non-performing loan” and a “performing loan” were created based on Self-Help’s tolerance for delinquency and loss. Keep in mind that the purpose of employing credit scoring at Self-Help is not to change the level of risk or performance of the overall loan portfolio, but rather to simplify the method for approving and denying loans in such a way to achieve similar decisions more efficiently. For this study, the following definitions were used:

Performing Loan: a loan that had:

- No delinquent payments, and
- No loan losses

Non-Performing Loan: a loan that had:

- More than 12 payments 60 days late, or
- More than 10 payments 90 days late, or
- More than 6 payments 120 days late, or
- More than 30 total delinquent payments, or
- Loan losses greater than 40% of the original loan balance

The definition of a performing loan clearly establishes a standard for loans that any lender should approve. 52% of the loans in the database met this definition of a performing loan. The definition of a non-performing loan acknowledges Self-Help’s practice of maintaining a loan portfolio in

which there is always a high amount of delinquencies, and only eliminates loans that are chronically delinquent or have incurred substantial loan losses. 18% of the loans in the database met this definition of a non-performing loan.

### **Assessment of Correlation: Regression Analysis**

Regression analysis was next applied to these data to determine if there are significant statistical relationships between underwriting factors and loan delinquency. Regression tests for correlations between dependent and independent variables, but does not necessarily prove causality. Thus we may find independent variables that are related to loan delinquency but it may not mean that those variables are the direct cause of delinquency. However, for this study's purpose, causation is not crucial; the goal is simply to identify those underwriting factors that are strongly associated with delinquency. Regression is also a process of determining probability of correlation: there remains the possibility of outliers that do not follow the norm. Thus there could be borrowers with very low credit scores or unprofitable businesses that are never delinquent. Be that as it may, regression can provide powerful insights into underwriting methodologies that casual observation cannot.

This first regression employed looked for associations between the various underwriting factors and the dependent variable, non-performing loans (as defined above). That is, the analysis pointed to key underwriting factors that were closely related to those loans defined as non-performing. The purpose of this regression is to help Self-Help eliminate future non-performing loans from its portfolio by rejecting them beforehand. Ordinal logistic regression analysis was used for this study because the dependent variable is a binary variable; a loan is either non-performing or it is not. The results showed that there are several key factors that are associated with non-performance.

A series of regressions were run to determine the combination of factors that were most closely associated with the dependent variable, non-performing loans. In each of the regressions run, one underwriting factor (independent variable) stood out as consistently highly associated with non-performance: Beacon score. Other significant factors are college education, homeownership, business profitability, co-borrower's Beacon score, and full-time management. This model produced a strong statistical fit: the probability of getting these results by chance alone is less than 1.08% (See Appendix C).

Beacon score (the consumer credit score developed by Fair Isaac and used by Equifax credit bureau) is by far the most predictive of non-performance. The presence of a business principal (usually the owner and manager of the businesses) with a undergraduate college degree was second in significance. Closely following these two factors are "homeownership" (whether the principal borrower owns his or her home) and "is the business profitable" (a yes/no answer based on the firm's existing financial condition) and the Beacon score of the loan's co-borrower (most loans do not have more than one personal borrower, thus this variable is not present in all loans). Each of these factors had an inverse relationship to non-performance. That is, lower Beacon scores, the lack of a college-educated manager, borrowers that were not homeowners were more likely to be associated with non-performing loans. Only one factor had a positive correlation with non-performance, and that was full-time management; the presence of a full-time manager was more likely to be associated with non-performance. This may seem to be counter intuitive,

but it may be related to the fact that most of the loans in the study were made to very small businesses. These borrowers may have a higher chance of paying their loan if they held a job while managing the business part-time.

This regression model was tested against various existing Self-Help loan applications, to determine if it predicted results that made sense. Using the parameter estimates generated by this model, probability factors (p values) were calculated for a variety of loans. It appears that using a p value of 60 or greater, Self-Help could successfully screen out non-performing loans from applications using this model. That is, using these independent variables, Self-Help could screen out loan applications that had a greater than 60% probability of meeting the stringent definition of non-performing loan. See Attachment D for a limited illustration of this test.

A second batch of regressions was also run to answer the same question in reverse: what factors are highly correlated with performing loans? In this case, a different independent variable, performing loans, was used to identify loan applications which Self-Help should always accept. These are loans that have never been delinquent and have never experienced loan losses. About 52% of the loans in the database met this criteria.

The results were very similar to non-performing loan regression model. Beacon score was the most predictive dependent variable, followed by college education, homeownership, debt/income ratio and co-borrower beacon score. The Beacon score of a co-borrower (either a spouse or an unrelated individual that agrees to assume liability for the loan with the business owner) had more significance in these regressions than in the non-performing models. Debt/income, which is the ratio of personal debt to personal income of the principal borrower, was a more significant factor, and the managing full-time factor dropped out as a significant factor (See Attachment C).

This regression model for performing loans was tested against a series of real loans and again, the relationship appeared to hold. Probability factors of 60 or greater would successfully identify loans that Self-Help should approve. Attachment D shows a sampling of real Self-Help loans applied to this model with their resultant p scores.

### **Analysis of Loan Decision Variables**

The strength of the consumer Beacon credit score in predicting loan performance is consistent with the experience of Fair Isaac and banks in their credit scoring methodologies. However, it is impossible to compare this study's findings with bank scoring models because those models are proprietary and the factors and their regression scores are not available. The literature research does indicate that consumer credit factors are the heart of bank scoring systems, which would indicate that Beacon scores have a stronger correlation to performing loans for bank portfolios than for Self-Help's portfolio. It appears that there must be other factors that are more associated with loan performance with Self-Help's business borrowers since Beacon score alone is not highly predictive. Indeed, this finding is consistent with the belief among CDFIs that bank underwriting has its limitations in approving small business loans in a community development setting. The other significant variables are not surprising, given Self-Help's experience with small business loan performance.

The cluster of management-oriented factors has some surprises in it. Management capability and experience is currently one of five major underwriting criteria used by Self-Help. Yet, in this study, almost all of these management-related factors have very little statistical association with loan performance. The importance of educational attainment of the principal borrower, and specifically having obtained an undergraduate degree, was not expected to have the highest correlation of the management factors. Interestingly, the attainment of an associate degree or a graduate degree makes very little difference in loan repayment; it is only a bachelor's degree that correlates highly. Other capability factors such as industry experience, management experience, supervisory experience and the preparation of a business plan have very low associations with loan repayment. These results could possibly be related to the omitted variable problem; the variables chosen to measure management capability may not be the best indicators. As mentioned earlier, the fact that companies that had full-time managers are more likely to be associated with delinquency than those with part-time managers was also a surprise..

Indicators of business financial condition were also mostly insignificant as predictors of loan performance. A positive response to the "is the business profitable" factor had a weak inverse association with non-performance, but other of these factors had insignificant correlation. This finding also confirms the bank scoring experience and Fair Isaac's exclusion of business financial data in their models. Self-Help uses these financial indicators in its current underwriting process, which may be unwarranted. On the other hand, it is possible that more accurate business indicators would change this result, if better information can be obtained.

Indicators of personal financial condition (not including personal credit history) are also fairly insignificant. Only the factor "homeownership" is positively related to loan performance (that is, borrowers who are homeowners are more likely to have performing loans and those that aren't homeowners as correlated to non-performing loans). This finding is consistent with the developmental theory that underpins Self-Help's mission – that the ability to accumulate wealth is a primary engine of economic success. Since equity in one's home is the primary way lower-income households accumulate wealth, it appears that Self-Help's focus on homeownership and wealth creation is appropriate. The other personal financial condition variables are not significant, with the exception of the often-used debt-to-income ratio, which showed some significance in predicting performing loans. It is possible that better information might be obtained to get a more accurate financial information to test these variable more rigorously, or perhaps there are another financial indicators that would do a better job of predicting loan repayment.

Self-Help often secures its business loans with personal and business collateral, and these factors were assessed in the regression as well. Collateral is mainly a means for obtaining repayment in cases of default, but there could be a relationship between the presence of collateral and loan performance. Only the factor "other collateral" (the presence of a lien against business' account, inventory and equipment) showed any statistical relationship at all, but a very weak one. Self-Help often places liens on these assets as a means of conveying to borrowers that repayment is important. Often in smaller loans the assets are not valuable enough to liquidate in the case of default, but it is suspected that the liens have a psychological effect on the borrower. It appears that this theory may have some validity. Interestingly, liens against homes and business real estate did not have nearly as much correlation with loan performance.

The co-borrower factor comes into play only for those loans in which a spouse or un-related individual signed the loan as a co-borrower. This was the case in 41% of the loans in the database. As expected, the presence of a co-borrower with good credit is associated with performing loans, and the lack of a co-borrower with non-performing loans. It is only significant if the beacon is fairly high – above 600. Otherwise, there is little impact on the overall p score.

In general, these regressions model represents a very stripped down version of Self-Help’s judgment-based system of underwriting, which is not surprising. Hopefully, with additional fine-tuning, a similar model can be developed that can predict loan performance with a higher degree of confidence.

### **Shortcomings of the Scoring Model**

The regressions using these 32 loan decision factors was not able to produce a model as predictive as the ones used by banks. This model could be employed at Self-Help to approve the very best loan applications and reject the worst ones. The “gray area” between automatic approval and rejection is significant. These loans in the gray area will still require the scrutiny by loan officers and underwriters because they cannot be accurately classified as a denial or approval by this scoring model. It is estimated that only 30% of all loan approvals can be approved by the scoring model. Since this database did not include denied loans, it is difficult to estimate the proportion of loans that will be denied using this model.

There are several reasons why this model cannot be used in 100% of all loan decisions. First, the data is not adequate for the task. As mentioned earlier, this database does not include all factors that are used by Self-Help for making its loan decision. One of the most important of these factors is the character assessment of the borrowers. This qualitative assessment, which is performed through interviews and other interaction with the applicants, was not included as one of the quantitative loan decision variables. It may be possible to create numeric score that captures the degree to which applicants have character traits of honesty and entrepreneurial talent, but it wasn’t represented in these regression models. There are likely to be other omitted variables that reduce the overall predictive value of these models.

Another factor that reduces the fit of these models is the presence of “dirty” data. Data contained in several of the factors (specifically personal debt/income ratio, debt coverage ratio, profitability of businesses, business net worth to asset ratio and personal net worth) that could be erroneous due to the imperfect quality of the data provided by applicants. Typically loan underwriters take this into consideration when assessing applications, and make adjustments in their decisions accordingly. A regression is not able to make such adjustments. Since these “dirty” factors are indicators of business and personal financial condition, it is possible that these factors are could be more or less statistically significant than indicated in the regressions. Only more accurate information would solve this problem. This is a problem that banks face even with their more seasoned and experienced small business applicants, which is why most credit scoring models do not even request business or personal financial information in their applications.

Lastly, this analysis suffers from a lack of size. Commercial loan scoring systems are based on models that include the performance of thousands of loans. Self-Help has one of the largest

databases for this type of studies among CDFIs, but it is woefully small for the purpose of performing statistically significant regression analysis.

The presence of omitted variables and inaccurate data, the small size of the database, and perhaps the influence of other factors, meant that it is not possible to construct a formal credit scoring model that is as rigorous as those used by banks. However, this analysis does provide Self-Help a working model that could be useful for making loan decisions for the is still instructive to those interested in devising simpler and less time-consuming loan approval processes.

## IV. NEXT STEPS AND CONCLUSION

This study tested the applicability of credit scoring to Self-Help's small business loan approval/denial process. The model developed has predictive capabilities, but not to the degree that would enable Self-Help to convert to a credit scoring system immediately. However Self-Help, or any other CDFI that was interested in employing a credit scoring system, can take one or more next steps, which are:

- Begin testing the proposed credit scoring model immediately on existing loans
- Develop a more comprehensive and accurate database of underwriting criteria
- Create a more rigorous credit scoring model using the improved database.

Self-Help could use the existing model to run side-by-side with its judgment-based underwriting system to compare the results. Credit scores of all small business loan applications can be collected for several years. Differences in judgment-based and credit scored decisions can be compared to look for patterns. Loan performance can be tracked over time to determine which system is more accurate in selecting loans. More importantly, Self-Help can start to collect scores for loans it denies. One of the biggest void in this study's database is the lack of data on loans that were denied. Since one of the goals of the study is to create a score that would assist in denying loan applications, additional data on denied loans would improve the model considerably by providing a large sample of loans that are at the low end of the credit quality scale.

Simultaneous with the testing of the existing model, additional efforts should be made to improve the quality and scope of the data collected on individual loans. As mentioned earlier, if some of the calculated factors (e.g. debt/income ratios) were collected in a more consistent and accurate manner, their usefulness in predicting performance would be enhanced. Self-Help can set about to standardize the collection of this data to improve data quality. In addition, better measures for some of the factors may also improve the model. For example, Self-Help does not have a direct method for measuring the quality and capability of business management, yet it based much of its judgment-based underwriting decisions on this factor. A better measure of management capability may make a credit scoring model more accurate.

Lastly, a much larger database would offer the greatest improvement to the model. Self-Help's universe of small business loans will always be very small. Credit scoring models built for commercial banks involve thousands of loans; the more available, the better the model. A project that combined small business loan data from several larger CDFIS would be ideal, although difficult to arrange.

Community Development Financial Institutions have successfully applied the best practices and technologies of the conventional banking sector for the benefit of low-income communities. The possibility of reaping the benefits of small business credit scoring remains an illusive goal for CDFIs, but one that is not outside their reach.

Commercial banks and non-bank small business lenders have garnered huge cost and marketing benefits from the use of credit scoring. It appears that banks that use credit scoring have

benefited from lower underwriting and marketing costs, a geographic increase in market area, and better risk management. Businesses have more options for borrowing small amounts, receive much faster decisions, and, for more marginal businesses, have access to conventional bank credit for the first time.

At the present time, CDFIs are not able to simply adapt existing credit scoring models used by banks. The types of data used by these models are not available for most CDFI business customers. For the same reason, the banks' practice of identifying and pre-approving credit for potential borrowers through third-party data sources is not possible for CDFIs at this time. CDFIs will have to modify these models to make them work for their markets.

Credit scoring will never entirely replace judgment-based underwriting at CDFIs. However, it can be used to select the best and worst loan applications. It appears that the biggest benefit to CDFIs will be in the efficient determination of loan denials. The time saved by not spending as much as 60% of a CDFIs staff time on meeting with, analyzing and denying loan applications can be better used to focus on those applicants that can be assisted by staff.

Credit scoring could help CDFIs address many of the barriers they face in expanding their services to disadvantaged small businesses. There is much work to be done to craft a way for CDFIs to successfully bridge the gulf between conventional credit scoring models and a model that will work equally well for the CDFI market. But if the gulf can be bridged, the benefits to CDFIs and their small business customers will be great.

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**ATTACHMENT A**  
**SELF-HELP BUSINESS LOAN DATABASE VARIABLES**

<b>Fields</b>	<b>Field Parameters</b>
<b>Loan Decision Variables</b>	
<u>Management Capacity</u>	
1 Business Ownership	1 if mgmt owned this or other business for more than 2 year, 0 if not
2 Industry Experience	1 if mgmt has previous experience in same industry, 0 if not
3 Supervisory Experience	1 if mgmt has previous mgmt/supervisory experience, 0 if not
4 Business Plan	1 if business plan was prepared, 0 if not
5 Managing Full-Time	1 if mgmt is working full-time in this business, 0 if not
6 Education: College	1 if graduate of 4-year college, 0 if not
7 Education: Community College	1 if graduate of 2-year college, 0 if not
8 Education: Graduate	1 if received graduate degree, 0 if not
<u>Business Financial Condition</u>	
9 Debt Coverage	Business EBITA divided by total debt payments
10 Business Net Worth	Adjusted business net worth divided by adjusted total business assets
11 Cash Injection	Amount of cash invested in business at time of SH loan
12 Is Business Profitable	1 if business was profitable in last full year, 0 if not
<u>Personal Financial Condition</u>	
13 Debt/Income	Primary borrower's monthly personal debt payments divided by
14 Cash	Total money in primary borrower's checking and savings accounts
15 Personal Net Worth	Adjusted net worth of primary borrower
16 Homeowner?	1 if primary borrower is a homeowner, 0 if not
<u>Personal Credit History</u>	
17 Beacon Score	Primary borrower's Equifax Beacon Score
18 Delinquent 90	Number of times primary borrower has been 90 days late on current outstanding debts, from credit report
19 Delinquent 60	Number of times primary borrower has been 60 days late on current outstanding debts, from credit report
20 Delinquent 30	Number of times primary borrower has been 30 days late on current outstanding debts, from credit report
21 Bankruptcy New	1 if primary borrower is currently in bankruptcy, 0 if not, from credit report
22 Bankruptcy Old	1 if primary borrower has a discharged bankruptcy, 0 if not, from credit report
23 # Judgments	Number of judgments >\$1,000 on primary borrower's credit report
24 # Collections	Number of collections >\$1,000 on primary borrower's credit report
25 # Liens	Number of liens on primary borrower's credit report
<u>Collateral/Co-Borrower Factors</u>	
26 R/E Collateral - home	Outstanding balance of all loans outstanding on home divided by estimated value of home
27 R/e Collateral - rental	Outstanding balance of all loans outstanding on investment property divided by estimated value of property
28 Share Security	SH loan divided by amount of cash securing loan
29 Other Collateral	1 if collateral other than real estate and shares used, 2 if not
30 Spouse Co-Borrower	1 if spouse co-signed the note, 0 if not

31 Other Co-Borrower	1 if individual other than spouse co-signed the note, 0 if not
32 Co-Borrower Beacon	Beacon Score of co-borrower
<b>Loan Descriptors</b>	
33 Control Number	1,6,101.103,95,96,98,99
34 Number	key identifier for loan
35 Amount	Original amount of SH loan
36 Closing Date	Date SH loan was closed and disbursed
37 Balance	Outstanding balance of SH loan on 6/30/02; blank if paid off earlier
38 Partner	Code for any formal lending partner
<b>Demographic Variables</b>	
39 Ethnicity	Race of primary borrower: 1 African American 2 Hispanic/Latino 3 Native American 4 Asian 5 Other ethnic minority 6 Minority, but no further info available 7 White: non-minority
40 Woman	1 if business is woman-owned; 1 or no-answer if not
41 Income	Last year's gross household income of primary borrower
42 HH Size	Number of persons in primary borrower's household
43 Start Year	Year the business began operations
<b>Loan Performance Factors</b>	
44 30 Days Late	Number of times borrower 30 days late on SH loan
45 60 Days Late	Number of times borrower 60 days late on SH loan
46 90 Days Late	Number of times borrower 90 days late on SH loan
47 120 Days Late	Number of times borrower 120 days late on SH loan
48 Total Delinquency	Total number of times borrower late on SH loan
49 Charge Off	Gross amount of funds lost on loan when charged off
50 Non-Performing	See report for definition
51 Performing	See report for definition

**APPENDIX B  
INDEPENDENT VARIABLE STATISTICAL PROFILE**

<b>Underwriting Variables</b>	<b>Count</b>	<b>Mean</b>	<b>Median</b>	<b>Standard Deviation</b>
Business Ownership	700	.431	-	.495
Industry Experience	555	.726	-	.446
Supervisory Experience	551	.388	-	.487
Business Plan	618	.356	-	.479
Managing Full Time	662	.778	-	.416
Education: College Degree	383	.520	-	.500
Education: Comm College Degree	384	.247	-	.431
Education: Graduate Degree	382	.115	-	.319
Debt Coverage	446	3.784	2.46	4.521
Business Net Worth	343	.361	.33	.831
Cash Injection	726	3314	0	12970
Is Business Profitable	324	.620	-	.485
Debt/Income	563	.428	.36	1.576
Cash	681	5222	1200	14547
Personal Net Worth	661	59675	20000	109033
Homeowner	572	.685	-	.464
Beacon Score	479	624	619	64.18
Delinquent 90	687	.755	0	1.73
Delinquent 60	687	.116	0	.515
Delinquent 30	687	.364	0	1.377
Bankruptcy New	692	.051	0	.775
Bankruptcy Old	692	.059	0	.236
# Judgments	691	.153	0	.481
# Collections	691	.111	0	.424
# Liens	691	.129	0	.581
Real Estate LTV -home	615	.271	0	.497
Real Estate LTV- rental	616	.159	0	.387
Share Security LTV	617	.364	0	2.072
Other Collateral	615	.714	-	.473
Spouse Co-Borrower	705	.472	-	.499
Other Co-Borrower	707	.226	-	.418
Co-Borrower Beacon	306	649	646	66.6
<b>Loan Descriptors Variables</b>				
Loan Amount	747	19944	10000	22746
Loan Balance				
<b>Loan Performance Variables</b>				
# Times 30 Days Late	750	1.855	0	3.614
# Times 60 Days Late	750	.993	0	2.227
# Times 90 Days Late	750	.624	0	1.640
# Times 120 Days Late	750	5.433	0	15.751
# Times All Delinquencies	750	8.899	0	18.199
Charge Off Amount	750	1.08	0	0

**APPENDIX C  
ORDINAL LOGISTIC REGRESSION MODELS**

<b>Ordinal Logistic Fit for Performing Loans</b>				
<b>Whole Model Test</b>				
<b>Model</b>	<b>-LogLikelihood</b>	<b>DF</b>	<b>ChiSquare</b>	<b>Prob&gt;ChiSq</b>
Difference	13.670101	5	27.3402	<.0001
Full	69.490893			
Reduced	83.160994			
RSquare (U)		0.1644		
Observations (or Sum Wgts)		120		
Converged by Objective				

<b>Lack of Fit</b>			
<b>Source</b>	<b>DF</b>	<b>-LogLikelihood</b>	<b>ChiSquare</b>
Lack Of Fit	114	69.490893	138.9818
Saturated	119	0.000000	Prob>ChiSq
Fitted	5	69.490893	0.0559

<b>Parameter Estimates</b>				
<b>Term</b>	<b>Estimate</b>	<b>Std Error</b>	<b>ChiSquare</b>	<b>Prob&gt;ChiSq</b>
Intercept[1]	-10.041861	2.6163295	14.73	0.0001
education college	0.72830858	0.3939212	3.42	0.0645
beacon score	0.00792631	0.0039216	4.09	0.0433
homeowner?	0.8261866	0.4613814	3.21	0.0733
debt/income	-1.306618	0.5182249	6.36	0.0117
coborrower beacon	0.00690013	0.0039787	3.01	0.0829

<b>Effect Wald Tests</b>				
<b>Source</b>	<b>Nparm</b>	<b>DF</b>	<b>Wald ChiSquare</b>	<b>Pro&gt;ChiSq</b>
education college	1	1	3.41831476	0.0645
beacon score	1	1	4.08526617	0.0433
homeowner?	1	1	3.20653646	0.0733
debt/income	1	1	6.35712468	0.0137
coborrower beacon	1	1	3.00775642	0.0829

**Ordinal Logistic Fit For Nonperforming Loans**

**Whole Model Test**

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	8.313054	6	16.62611	0.0108
Full	36.317335			
Reduced	44.630389			
RSquare (U)		0.1863		
Observations (or Sum Wgts)		95		
Converged by Gradient				

**Lack Of Fit**

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	88	36.317335	72.63467
Saturated	94	0.000000	Prob>ChiSq
Fitted	6	36.317335	0.8815

**Parameter Estimates**

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept[1]	4.74834338	3.8503447	1.52	0.2175
education college	-1.3586114	0.6002278	5.12	0.0236
beacon score	-0.0062951	0.0049321	1.63	0.2018
homeowner?	0.4733672	0.5886035	0.65	0.4213
managing full-time	1.4640503	0.6074052	5.81	0.0159
Is business profitable	-0.5258104	0.5751951	0.84	0.3606
coborrower beacon	-0.0039187	0.0054088	0.52	0.4688

**Effect Wald Tests**

Source	Nparm	DF	Wald ChiSquare	Prob>ChiSq
education college	1	1	5.12340053	0.0236
beacon score	1	1	1.62910553	0.2018
homeowner?	1	1	0.64677097	0.4213
managing full-time	1	1	5.80971791	0.0159
Is business profitable?	1	1	0.83565715	0.3606
coborrower beacon	1	1	0.52491144	0.4688

**APPENDIX D**  
**ILLUSTRATION OF PROBABILITY SCORES FOR SAMPLE LOANS**

**Loan Approval**

Factors	Loan #1	Loan #2	Loan #3	Loan #4	Loan #5	Loan #6	Loan #7
Beacon	625	600	600	625	675	600	675
College Educ	yes	yes	yes	no	no	yes	yes
Homeowner	yes	yes	yes	yes	yes	yes	no
Debt/Income	20%	20%	20%	20%	10%	11%	10%
Co-Borrow Beacon	none	none	635	none	675	none	none
Prob score	0.64	0.57	0.60	0.47	0.60	0.60	0.60
( $>.59 =$ approve)							
Approve or Not	Yes	No	Yes	No	Yes	Yes	Yes

**Loan Denial**

Factors	Loan #1	Loan #2	Loan #3	Loan #4	Loan #5	Loan #6
Beacon	550	550	550	525	500	500
College Educ	no	no	0	no	no	no
Homeowner	no	no	0	yes	yes	yes
Full-time Mgmt	yes	yes	yes	yes	yes	yes
Business Profitable	no	no	n/a	no	no	no
Co-Borrow Beacon	none	610	none	none	none	575
Prob score	0.63	0.59	0.48	0.58	0.60	0.58
( $>.59 =$ deny)						
Deny or Not	Yes	No	No	No	Yes	No