Measuring the Likelihood of Small Business Loan Default:
Community Development Financial Institutions (CDFIs) and the use of Credit-Scoring to Minimize Default Risk[1]

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Abstract

Community development financial institutions (CDFIs) provide financial services to underserved markets and populations. Using small business loan portfolio data from a national CDFI, this paper identifies the specific borrower, lender, and loan characteristics and changes in economic conditions that increase the likelihood of default. These results lay the foundation for an in-house credit-scoring model, which could decrease the CDFI's underwriting costs while maintaining their social mission. Credit-scoring models help CDFIs quantify their risk, which often allows them to extend more credit in the small business community.*

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I. Introduction

Community development financial institutions (CDFIs) provide financial services to underserved markets and populations. In theory, credit needs would be appropriately priced in a perfectly competitive market, but in reality, many businesses and consumers may not be served effectively by traditional institutions due to high transaction costs and asymmetric information. To counter this problem, CDFIs extend more credit to "mission" borrowers, usually consisting of women, minorities, and/or low-wealth individuals. The first CDFIs were created out of the Johnson Administration's "War on Poverty Campaign" in the 1960s and 1970s. Now, CDFI investors come from a broad range of backgrounds, and some are lured to CDFIs purely for their expected returns rather than for a social purpose. As CDFIs in the United States expand to larger and more competitive markets, many want to better manage the risk in their portfolios.

CDFIs offer a range of financial services, covering both residential and commercial loans, for economically disadvantaged communities. The data in this paper are from X CDFI, which is one of the largest CDFIs in the United States.[2] Using their portfolio, I identify the characteristics associated with SBL repayment. Building on an internal study at X, I isolate the borrower, lender, loan and macroeconomic characteristics that affect the likelihood of default. These results lay the foundations for an in-house credit-scoring model, which has the potential to increase consistency and reduce the costs of underwriting a loan. Credit-scoring models allow banks to quantify risk, which encourages better lending practices, and often extend more credit in the small business community.

[2] The CDFI has requested to keep its identity anonymous.

However, credit-scoring may also force the CDFI to drift away from its mission clientele if the mission borrowers are not deemed as credit-worthy.[3] CDFIs use non-traditional financial instruments and cater to a different type of clientele compared to traditional banking institutions, which do not face these mission borrower requirements. The current literature lacks a cohesive body of work that identifies the characteristics of a risky loan for a CDFI-borrower population. In addition, there is a lack of information concerning CDFI credit-scoring methodologies or expected scoring outputs for a given small business loan portfolio. In part, this is because it is rare and expensive for a CDFI to develop credit-scoring technologies.

The literature review in Section II is comprised of three parts. Section IIA of the literature review discusses the idea that extending credit to the poor and underserved markets can be profitable, a discovery often credited to microfinance institutions (MFIs). When lenders underwrite loans to these markets, they often want to identify risky loan characteristics, which are discussed in Section IIB. Section IIC explains how loan default models can be turned into credit scores, which can improve the efficiency of small business loan origination. Credit-scoring models help banks identify characteristics that contribute to loan defaults and weight those characteristics according to their relative significance. Section III provides the theoretical framework to build a credit-scoring method that minimizes loan defaults. The data in this paper are discussed in Section IV, and the empirical specifications are laid out in Section V. Section VI provides a working-world credit-scoring application of the model developed in Section V. The concluding remarks are in Section VII.

[3] Mission clientele, as described previously, includes women, minorities, and low-wealth individuals.

II. **Literature Review**

a. Discovering underserved markets across the world

In 1976, frustrated with the trickle-down approach to economic development, Muhammad Yunus extended credit to the poorest of the poor as a social experiment. Yunus and his bank Grameen, headquartered in Bangladesh, are often credited as being among the first microfinance banks, institutions that have been able to tap into the hidden wealth of the poor (Easton, 2005). The poorest people are often considered "unbankable," because they do not have characteristics of traditional borrowers, such as reliable credit histories or high levels of collateral.

Over the past thirty years, many microfinance institutions (MFIs) have emerged across the globe, and compared to traditional banks, many MFIs boast high repayment rates from borrowers without formal credit histories (Morduch, 1999). Some of these rates, however, are deceiving. Although institutions like Grameen report repayment rates averaging 97-98%, Jonathan Morduch asserts that the relevant rate is about 92%. In addition, although Grameen charges interest rates of 20% per year, it would have to charge around 32% in order to become fully financially sustainable[4] (Morduch, 1999). Banks often need to charge large interest rates because small loans can be expensive to service and do not return large profits per loan.

The reason Grameen can survive even though it charges borrowers low interest rates is because it depends on subsidies, a topic that has garnered warranted suspicion over the course of microfinance's increased popularity. In the United States, many CDFIs also charge low interest

[4] A firm achieves profitability when its revenues are greater than its costs. A firm may be "profitable" with subsidies or grants, but it may not be "financially sustainable" because without its subsidies or grants it would go under. Financial sustainability is a more contentious issue in the microfinance world. Especially if the firm can depend on reliable and continuous grants and subsidies, for instance from the government, a firm can be continually profitable without being financially sustainable.

rates because their loans are also subsidized by the government or socially-conscious investors.[5] Some CDFIs are profitable, some are profitable because of subsidies, and some not profitable but still carry on due to subsidies, including cross-subsidies from profitable activities, and investor support for their "mission."

Although many CDFI are inspired by microfinance initiatives in the developing world, they have operational differences in the United States, which is the focus of this paper. A MFI is a general term for an institution that provides financial services to low-income clientele who lack access to traditional banking sources. A CDFI is an American financial institution that also provides financial services to underserved markets. CDFIs often engage in more advanced services than MFIs, and CDFIs are certified by the Community Development Financial Institutions Fund at the U.S. Department of the Treasury. One prominent distinction is that a majority of CDFIs in the U.S. do not engage in group lending as a method to minimize asymmetric information like the MFIs in the developing world.

Gary Painter and Shui-Yan Tang (2001) study the microcredit challenge in California. They find that most of the MFIs are not close to reaching any measure of financial sustainability.[6] They attribute part of this problem to excessive overhead costs – some of which can be three times the size of the loan amounts. These overhead costs can include the time a loan officer spends investigating the borrower's background, any paperwork – both in-house and for the government – compiled during the loan process, and other administrative tasks. They also note that unlike in the developing world, in the U.S., an individual's ability to obtain future credit

[5] For example, many CDFIs in fact charge interest rates that are based on specific programs, rather than on the perceived risk of the borrower. This is discussed in greater detail in the data section.

[6] In this study, the MFIs were limited to institutions whose loans were $25,000 or less. The portfolios were also relatively small and they had a relatively small underwriting team. The CDFI I am working with has a much larger range for its loans and a larger and more sophisticated portfolio. These are significant differences.

is less critical for survival, because most people have the ability to fall back on the government welfare system (Painter and Tang 2001). In other words, a CDFI-borrower population is significantly different from an MFI's borrowers in the developing world, and each would have a different set of risks. The CDFI small business banks, which are designed for the low-income entrepreneur, are also significantly different from traditional commercial banks. They develop special relationships and localized expertise that larger banks cannot provide, which makes the small business credit markets vast, differentiated and segmented (Ou, 2005).

b. Identifying strong borrowers versus weak ones

Because the current literature lacks a cohesive analysis of CDFI loan default characteristics, this section identifies risky loan characteristics in populations that are similar to CDFIs. Many institutions that service small business loans do not want or have the ability to quantitatively track risk, due to the high costs or concern that it would compromise their mission.

All lenders do some sort of risk analysis before underwriting a loan. The two types of risk analysis are quantitative and qualitative. Loan officers perform a qualitative risk analysis when they interview the potential borrower, look over the business plan (if available) and review past financial history. Quantitative risk analyses are more expensive and time consuming, because they require keeping track of loan data both during loan origination and monitoring. Quantitative analyses are often combined to create a "credit score," which quantifies the predicted risk of the borrower. Each credit-scoring model provides the best predictions when it is individually developed for a particular bank's loans and lending practices. This type of credit-scoring is described in further detail in the next section.

The characteristics of risky loans differ between populations. This paper focuses on small business loans, which, unlike consumer loans, generally finance investment rather than consumption. One of the most predictive measurements of small business loan repayment is the personal credit score. Cowan and Cowan found that the borrower's personal credit history is often deemed more important and predictive of repayment than the business plan or feasibility of the idea (Cowan et al., 2006). Frame, Srinivan, and Woosley (2001) also find that the personal consumer credit history of small business borrowers is highly predictive of loan repayment, particularly for loans under $100,000.

Loretta Mester (1997), vice president and economist in the Research Department of the Philadelphia Fed, cites the applicant's monthly income, financial assets, outstanding debt, employment tenure, homeownership, and previous loan defaults or delinquencies as predictive of loan default for SBLs. Many CDFIs use Small Business Administration (SBA) guarantees when they underwrite SBLs. Dennis Glennon and Peter Nigro (2005) analyze SBA loan repayment and find that *defaults are time-sensitive* and are particularly affected by the changing economic climate during the life of the loan. The probability of default in their SBA dataset peaks after six to twelve months, which suggest that any model should include time-sensitive variables. In addition, they find that long-term loans are more sensitive to changes in the business cycle than short term loans. They also find that corporate structure (i.e. corporations, partnerships or sole proprietorships) has a large influence on the odds of default. Some papers even find that lending to better-off borrowers results in *higher* delinquency rates, suggesting that when borrowers have better alternatives, they value the program less (Wenner, 1995). This shows that a selection bias can arise if better-off borrowers go to institutions like CDFIs when they have riskier projects.

Hans Dellien and Mark Schreiner (2005) use recent microfinance data to identify twenty-one predictive indicators (listed in “rough order of importance”):

1. Days in the longest spell of arrears in the previous loan
2. Length of time as a client
3. Type of business
4. Age of applicant
5. Identity of the loan officer
6. Telephone ownership
7. Household structure
8. Years in business
9. Cash-on-hand
10. Number of scheduled installments
11. Years in the current residency
12. Number of installments in arrears in the previous loan
13. Number of installments paid-off early in the previous loan
14. Experience of the loan officer
15. Number of businesses run by the household
16. Days of delays between application and disbursement
17. Total assets
18. Days of rest after paying off the previous loan
19. Accounts receivable
20. Home ownership
21. Debt/equity ratio

Of note, Schreiner’s data come from affiliates of Women’s World Banking in Columbia and the Dominican Republic, which is a significantly different population than U.S. CDFI borrowers. However, his indicators provide some insight into characteristics that may influence borrowers in underserved markets. Additionally, many of these indicators may not be used by traditional U.S. banks in credit-scoring and may improve on the current models.

Many financial institutions that service underserved markets focus on gender when deciding to underwrite a loan, after realizing that female repayment rates are sometimes higher. For example, Grameen’s membership was 94% female by 1992, even though targeting women was not the initial social mission (Morduch, 1999). This rate can be deceiving because although Grameen claims that women are better borrowers, women may not be significantly different from men when controlling for other factors. The 94% also captures Grameen’s preference for working with women rather than men, which is part of their social mission.

X has worked on an internal research project within its commercial loan portfolio. The Kinat Report analyzes two data sets separately (SBA and non-SBA loans in X's portfolio) with loans that originated between 2002 and 2007. In the Small Business Administration loan (SBA) regression, the three best predictors of loan performance are (1) personal credit score, (2) owner management experience, and (3) length of existing business. Sixteen factors have no significant relationships.[7] I combine the same SBA and non-SBA data in this paper, supplement this dataset with additional macroeconomic variables, and use a different method for selecting the independent variables.

Although the popularity of microfinance in the developing world and CDFIs in the US seems to be growing exponentially, it does not mean that they are immune to the credit bubbles seen in other periods of economic exuberance. A recent *Wall Street Journal* article notes that as more private-equity funds and other foreign investors come to invest in the tiniest loans in the world, MFIs are having a harder time identifying qualified borrowers (Gokhale, 2009).

c. The adoption of credit-scoring technologies

After a CDFI develops a model to predict the best borrowers, the results of that model can be turned into an in-house credit score. Credit-scoring technology is another method to diminish the asymmetric information gap between the borrower and lender, which leads to a more efficient allocation of capital. Credit-scoring has been more widely adopted in traditional banks than in CDFIs, because CDFIs are concerned that they might "mission-drift away" from

[7] These factors are: Loan Amount, Borrower Net Worth, Projected Breakeven at time of loan, Year, Personal Income, Use of Proceeds, Guarantee Percentage, Personal D/I at time of loan (before X's loan), Equity investment of business owner, SBA Type, Personal debt-to-income at time of loan (including X's loan), Gender, Rural/urban dummy, Type Business (Restaurant, etc), and Race. .

their desired clientele if they use credit-scoring. To clarify, the term "credit-score" has two distinctly different meanings: [8]

A personal credit score: also known as a FICO score or Beacon score, measures an individual's personal consumer credit history (such as whether he or she has paid their bills on time and the amount of debt on their credit cards).	**In-house credit-scoring model**: These in-house models will often use a personal credit score combined with other variables such as management experience or the business's cash-flow. This statistical model identifies significant variables, applies relative weights to each, and provides an in-house "score."

In this paper, "credit-scoring" refers to the statistical in-house credit-scoring model rather than the personal FICO score. Often a bank will use the borrower's *personal consumer* FICO score when deciding to underwrite the borrower's *business* loan. Rarely does the bank have access to business credit scores, especially because most of these small businesses are start-ups or are in the early stage of development and the finances of the business are often tied with the personal finances of the owner.

Robert Schall (2003) asserts that the use of consumer credit-scoring models could have inherent racial or income biases because the reports are created from borrowing practices that are more common of white and middle-class neighborhoods. Unfortunately, although this statement could be plausible, it is difficult verify because most personal/consumer credit-scoring methods are proprietary and confidential. In 1997, Eugene Ludwig, the U.S. Comptroller of the Currencym warned that credit-scoring systems might be "flawed" due to the misuse of "overrides," which are manual approvals of a loan when the score recommends rejecting the loan or *vice versa*. He claims that this can create biases that have a disproportionate impact on

[8] Personal credit scores are often developed and standardized by a company, like Experian or Fair Isaac, and scores can be purchased by a bank. Technically, the Beacon score is used by Experian, and the FICO, which stands for Fair Isaac Corporation, was developed by Fair Isaac. The terms Beacon and FICO are often used interchangeably, although FICO has become more commonly used.

minorities (Green, 2000). This controversial statement has not been verified in academic economic literature.

Cowan et al. identify the differences between banks that often focus more on credit-scoring lending instead of pure "relationship" lending. They find that rural banks are less likely to adopt credit-scoring compared to their urban counterparts, indicating that rural banks specialize in the relationship lending (Cowen et al, 2006). Schall (2003) also identifies the difference between these banking characteristics, although he uses the phrases "credit-scoring" underwriting and "judgment-based" underwriting. The distinction between the two is important for a CDFI, because the judgment-based method is relatively costly and significantly more time consuming than an automated credit-scoring method.

Most CDFIs question the reliability of using only a pure credit-scoring method. Even if they do employ this statistical technology, they will often supplement it with a judgment-based recommendation. This proposal identifies the variables a bank would need for a credit-scoring model. These variables include (i) borrower-specific variables, such as gender or education level, (ii) loan-specific, such as size of the loan, (iii) business specific, such as industry, and (iv) macroeconomic variables. The relative importance of each of these variables in a credit-scoring model can be measured using the bank's portfolio. Although a credit score will never predict with certainty the likelihood of default for an individual loan, it does allow the firm to quantify relative risks for groups of borrowers (Mester, 1997).

CDFIs provide services for underserved markets, which can be profitable if the CDFI is able to identify the best borrowers. Although models for small business credit-scoring in the current economic literature exist, the literature lacks a theory for CDFI credit-scoring, which has a different set of constraints than traditional banks. Additionally, most credit-scoring methods are proprietary and many publications only reveal the theoretical components of a score and not the actual weight of each component.

III. Theoretical Framework

There are three takeaways from the literature review section that should be kept in mind as the theoretical framework for this paper is presented. (1) In the U.S., due to its desire to retain a social mission, CDFIs underwrite different types of small business loans (SBLs) than traditional banks. (2) Aside from personal FICO score, rarely does a set of predictive indicators for one population of SBLs also best predict a different population of SBLs – especially considering that CDFI borrowers are different from developing-world microfinance borrowers and from traditional small business borrowers. Finally (3), after a loan default model is developed for a specific population, it can be converted into a credit-scoring system to use on future loans for similar populations. The third takeaway is a business world application of the model created in (2).

This section explains the theoretical analysis behind the predictive indicators of loan default for CDFI SBLs. Four types of variables affect SBL default:

Borrower-Specific Characteristics	**Loan-Specific Characteristics**	**Lender-Specific Characteristics**	**Macroeconomic Variables**
Such as corporate structure, FICO score, education and industry	Such as guarantee percentage, loan amount, and interest rate	Such as loan-officer identity, loan-officer type, and region	Such as changes in the business cycle and in local unemployment

Because SBL default can be influenced by countless factors, I will briefly go through the most important influences and provide a table of predicted signs at the end of each section.

a. Borrower-specific characteristics

Table 1. Predicted signs of select borrower-specific characteristics

Dependent Variable: Strong/Good Loan

Independent Var	**Predicted Sign**	**Notes**
FICO score	+	Small business borrowers with good personal credit histories are more likely to repay their loans
Educational Experience	+	Borrower with more education will probably be able to pay back loans better
Management Experience	+	Borrowers with more management experience will likely run better businesses and pay back loans better
Race	+/-	There are conflicting results in the literature. It is more likely that race is correlated with one of the other measurements, such as FICO, income or education. It could also be correlated with relevant unobserved/omitted variables such as potential family support to pay back a loan.
Industry classification	+/-	Depends on the barriers to entry and the particular economic climate for each industry
Female	+/-	Some microfinance institutions and research claim that women pay back more often than men
Debt-to-income before loan	-	Borrowers with larger amounts of debt will probably have more difficulty paying back a loan
Length business	+	Older businesses tend to be more stable and probably can absorb negatives turns in the business cycle better than start-ups
Income, assets, material ownership	+	Borrowers with the ability to liquidate other assets to pay back the loan are more likely to be able to repay. **Note**: Ability to repay and desire to repay are not always the same. Wenner (1995) finds that wealthier borrowers are *less* likely to repay, perhaps because when borrower have better alternatives, they value the loan less.
Personal name on loan *(vs. business name on loan)*	+	A borrower will probably be less likely to default if the loan is in their name rather than in the business's name
Business structure *(e.g. corporation, partnership, sole proprietorship)*	+/-	Different business structures may have varying levels repayment rates

There are countless borrower variables that could influence loan default. For instance, unexpected personal changes, such as divorce or disease, could affect a small business owner's ability to repay. In addition, many of the variables listed above could be highly correlated, such as educational experience and management experience. Each CDFI would need to pick the variables that would best suit its portfolio and needs.

b. Loan-specific characteristics

Table 2. Predicted sign of select loan-specific variables

Dependent Variable: Strong/Good Loan

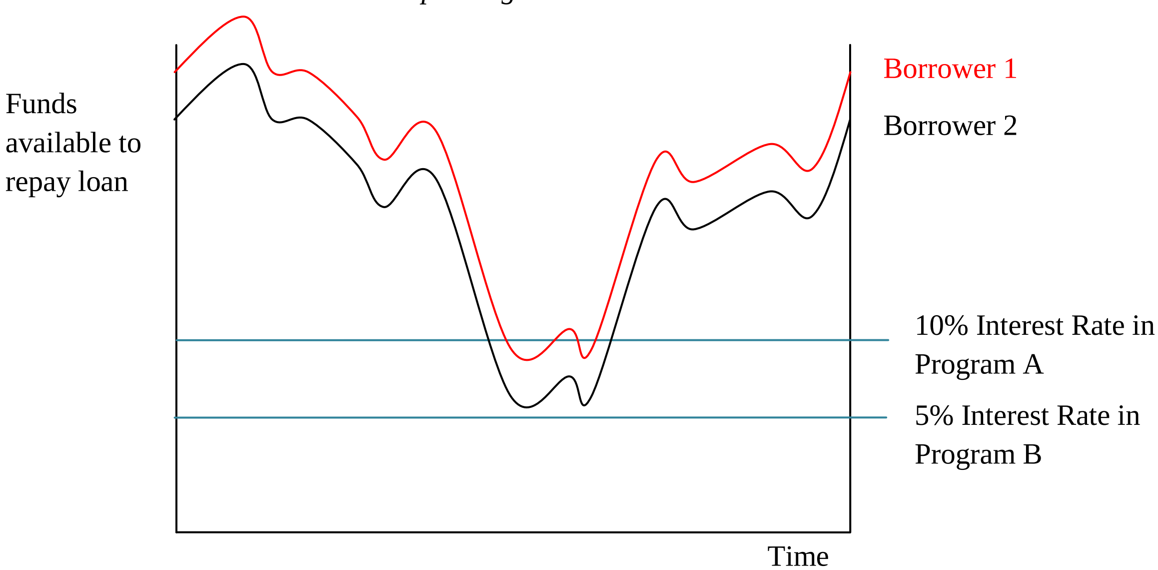
Independent Var	**Predicted Sign**	**Notes**
Loan amount	-	Larger loans are more difficult to pay off than smaller loans
Interest rate	-	Loans with high interest rates are harder to repay. Also, in many banks high interest rates indicate a riskier borrower (but not true if using program-based interest rates)
Interest rate deviation from prime	-	Measures how much of a premium on the interest rate the borrower could get than on the market (If using program-based pricing, the interest rates do not reflect the relative risk of the individual, and a premium variable could isolate the problem identified in *Figure 1, pg 16.*)
Variable interest rate *(dummy, variable=1, fixed=0)*	-	Variable rate loans that "float" the interest rate after a given period can provide an additional burden for the borrower. Most variable rate loans in the portfolio are defined as Fed Prime + a spread (e.g. 3%) and are updated monthly. Other variable rate loans have different updating criteria.
Age of loan	-	As a loan gets older, it has more opportunities to default
Government/Investor guarantee *(dummy, ex: SBA=1, non-SBA=0)*	-	Government guaranteed loans can help encourage more access to credit in the small business community. It is likely that loans with higher government backing are riskier[9]
Guarantee percentage	-	Same reason as above, and as the guarantee increases, the loan is probably given to a riskier borrower. Although the guarantee percentage decreases the burden on the bank, the bank often would not get paid if it does not try to collect from a loan in arrears (which minimizes moral hazard).

There are two ways to assign interest rates to a loan. First, the interest rate can be set as the "price" of a loan. Riskier borrowers have to pay higher interest rates. This is the conventional

[9] The Small Business Association (SBA) loan program is a government-backed program, which provides loan guarantees to eligible business through financial institutions, like CDFIs. The CDFI chooses the borrowers, and after approval, underwrites the loan. The SBA is contractually obliged to purchase the defaulted loans at a set guarantee level, which ranges from 50 to 85%.

approach, and is often referred to as "risk-based pricing." For a variety of reasons, which are heavily influenced by its social mission and by its investors, many CDFIs are obliged to price loans based on the individual programs with guidelines set by the program's investors. CDFIs can obtain capital at subsidized rates or through grants, and they are sometimes able to pass on these low interest rates to their borrowers. At X, most interest rates are program-based and not risk-based, although X sometimes has flexibility to change the rate. In general, this means that everyone who qualifies for program Y has to repay with interest rate Z_Y regardless of their risk profile. The CDFI's program-based interest rate method can affect the repayment rate.

Figure 1. *Similar borrowers may have different outcomes depending on their individual interest rates*



In Figure 1, Borrower 1 has almost the same characteristics as Borrower 2, but Borrower 1 always has an additional access to credit to repay the loan. Borrower 1 should obtain a higher credit score than 2. However, this can be misleading depending on the outcomes:

Event 1	**Loan Type**	**Outcome**	***Event 2***	**Loan Type**	**Outcome**
Borrower 1	Program A	Default	Borrower 1	Program B	No default
Borrower 2	Program B	No default	Borrower 2	Program A	Default

In Event 1, Borrower 1 defaults on the loan because she has a higher (more expensive) interest rate than Borrower 2, and she does not have the funds to repay (e.g. the "funds available to repay" is below the interest rate line). Borrower 2 would have also defaulted if he had this more expensive loan, but he does not default because he has a cheaper loan. Deceivingly, this outcome indicates that Borrower 2 is the optimal candidate, when in general Borrower 1 would be the better candidate because she has more funds available. The credit-scoring process should identify the best borrowers in the dataset and *not* the best borrowers for each loan type because loan types can change frequently. For this reason, the likelihood of default analysis needs to include either a variable for the program or the interest rate or both.

In addition, the macroeconomic climate likely affects types of loans a CDFI underwrites. Because some macroeconomic conditions affect both the dependent variable (SBL default) *and* independent variables (loan-specific characteristics), the model controls for this using interaction terms, which is discussed further in the empirical specification.

c. *Lender-specific characteristics*

Table 3. Predicted signs of select lender-specific variables

Dependent Variable: Strong/Good Loan

Independent Vars	Predicted Sign	Notes
Region	+/-	Regional loans may have different repayment rates
Loan officer	+/-	Loan officers have specialized skills and good loan officers will underwrite better loans for a borrower. They also may identify a loan that needs to be modified before it defaults.
Assets that must be lent in a given period or would be lost	-	Some CDFIs have time constrains on the assets in their portfolios. If they do not find borrowers for certain assets in a given period, those assets may be taken away.
Ability to modify a loan	+	If lender A has more resources on hand and can modify a failing loan more easily than lender B, lender A's loans are likely to default less often

Many of the lender-specific variables act as controls rather than as predictors of SBL default. In practice, these data can be difficult to capture. For instance, the relative strength of the loan officer might be complicated to interpret, especially if the loans in her portfolio are all part of an industry that was hit particularly by a recession. Furthermore, some loan officers might always handle troubled loans, even if they are highly-skilled and able to help many loans become strong.

d. Macroeconomic conditions

Table 4. Predicted sign of select macro-economic variables

Dependent Variable: Strong/Good Loan

Independent Vars	Predicted Sign	Notes
Absolute changes in the economic period *(Ex: peak unemployment rate)*	-	The absolute changes in the business cycle probably hurt small businesses more than gradual changes
Average changes in the economic period *(Ex: average unemployment rate)*	-	Sustained and lasting downturns in the economic cycle make loan repayment more difficult
Overall health of the economy *(Ex: S&P 500, CCI)*	+	Loans are probably easier to repay during strong economic cycles

Many of the macroeconomic variables are highly correlated and probably should not all be used in the same model. A CDFI should select the ones that are the best for its individual portfolio.

To analyze the relative importance of each of these variables on loan defaults, I analyze the data using three methods: OLS, logit (converted into odds ratios), and a multinomial logit. Mitchell Petersen and Raghuram Rajan (1994) use an OLS regression to analyze their loans. The small business loan default rate using an OLS model is the following:

$$P\left(\frac{SBL_i}{Default}\right) = \beta_0 + \beta_1 * borrower_i + \beta_2 * lender_i + \beta_3 * loan_i + \beta_4 * macro_i + \varepsilon_i \quad (1)$$

Where β_0 is the constant, ε is the error term, and loan, lender, borrower, and macroeconomic variables are all specific to the individual loan i. The benefit of an OLS regression is that the coefficients can be directly interpreted as the relative weights that influence loan defaults. The downside is that if the SBL default rate is binary, where good loans are equal to 1 and bad loans are equal to 0, OLS regressions can output values that are greater than 1 or less than 0, which are nonsensical probabilities.

A logit model solves this problem, because it will not predict probabilities that are greater than 1 or less than 0. The downside of a logit model is that the coefficients cannot be directly interpreted (unless converted into an odds ratio), which makes subsequent credit-scoring values more difficult to calculate. A logit model measures the probably of defaults as the following:

$$D_i^* = \beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i + \varepsilon_i. \tag{2}$$

Here, D_i^* is the SBL default rate, X_i contains borrower-specific variables, Y_i contains loan-specific variables, Z_i contains lender-specific variables, and M_i contains macroeconomic variables. The error is assumed to be distributed as a standard logistic. The borrower would default $(D_i = 1)$ if $(D_i^* \geq 0)$ and she would repay the loan $(D_i = 0)$ if $(D_i^* < 0)$. We can determine the default probability:

$$\begin{aligned} p_i &= \Pr(D_i = 1) \\ &= \Pr(D_i^* \geq 0) \\ &= \Pr(\beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i + \varepsilon_i \geq 0) \\ &= \Pr(+\varepsilon_i \geq -(\beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i + \varepsilon_i)) \\ &= 1 - F(-(\beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i + \varepsilon_i)) \end{aligned} \tag{3}$$

Where F is the cumulative density function for ε. For the logit model, this is specified as

$$\Pr(D_i = 1) = 1 - F(\beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i)$$

$$= \frac{1}{1+e^{-(\beta_0+ \beta_1 X_i+\beta_2 Y_i+ \beta_3 Z_i+\beta_4 M_i)}} \quad (4)$$

The probabilities from a logit model are between 0 and 1:

$$\Pr(D_i = 1) \rightarrow 0 \text{ as } \beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i \rightarrow -\infty \quad (5)$$

$$\Pr(D_i = 1) \rightarrow 1 \text{ as } \beta_0 + \beta_1 X_i + \beta_2 Y_i + \beta_3 Z_i + \beta_4 M_i \rightarrow \infty \quad (6)$$

This is a binary logit ("default" or "repaid"). If the dataset differentiates beyond two dependent variables, such as X's dataset, where there are three loan repayment options: *strong*, *medium*, or *weak* loans, a multinomial logit regression can be the best model. The multinomial logit regression for the model is:

$$Pr(D_i = Strong, Medium, or\ Weak) = F\left(\frac{\beta_0+ \beta_1 X_i+\beta_2 Y_i+ \beta_3 Z_i+\beta_4 M_i)}{\sigma}\right) \quad (7)$$

Where $D_i = S$ if the loan is strong, M if medium, W if weak, X_i contains borrower-specific variables, Y_i contains loan-specific variables, Z_i contains lender-specific variables, and M_i contains macroeconomic variables. The benefit of a multinomial regression is that a strong loan's influences are separately identified from a medium loan and from a weak loan. The drawback is that calculating a credit score using the multinomial logit method is also more difficult.

IV. **Data**

The methodology and data in this paper have been IRB approved. The data come from X CDFI's original loan files. All of the files are hard copies, and it took numerous people to compile the dataset. It can take twenty to forty-five minutes to identify and tally all of the required information for a loan file (Overstreet and Rubin 1996). The dataset contains 530 loans, which includes 229 SBA loans and 301 non-SBA loans. The S&P 500 information comes from Datastream, and the S&P values are linked to each loan depending on the date of origination. The local state-level unemployment rate data is from the Bureau of Labor Statistics.

Table 5. *Origination dates by loan program*

	SBA Loans			Non-SBA Loans			Combined Loans		
Origination Year	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.
2002	3	1.31	1.31	96	31.89	31.89	99	18.68	18.68
2003	32	13.97	15.28	103	34.22	66.11	135	25.47	44.15
2004	33	14.41	29.69	102	33.89	100	135	25.47	69.62
2005	34	14.85	44.54				34	6.42	76.04
2006	61	26.64	71.18				61	11.51	87.55
2007	66	28.82	100				66	12.45	100
Totals	***229***	***100***		***301***	***100***		***530***	***100***	

The non-SBA loans only originate between 2002 and 2004 in this dataset. Although X CDFI did underwrite non-SBA loans after 2004, the data is not yet in digital form. The unbalanced combined loan data will have controls to minimize the bias of the earlier origination dates of the non-SBA loans.

The definition measure of loan default is described in the following table:

Strong	Medium	Weak
Never delinquent	Ever 30+ days delinquent more than once	Ever 90+ days delinquent
Never modified	Ever 60+ days delinquent	Charged off
	Ever modified	

Notes:

- 30+, 60+, 90+: If 90+, is not counted as 30+ or 60+
- Loans modified for one month (these are mostly non-payment related) or delinquent one time for 30 days classified as “strong”

The loans in this dataset have a relatively high default rate. Around 26% of all of the loans are classified as “weak,” 34% are classified as “medium,” and only 39% are classified as strong. This data comes from a non-random sample, which over emphasizes weak loans. This is discussed in further detail at the end of this section. Table 6 outlines the frequencies and cumulative percentage of the loans.

Table 6. *Loan strength by loan program (as of October 2009)*

Loan Strength	SBA Loans Freq.	SBA Loans Percent	non-SBA Loans Freq.	non-SBA Loans Percent	Combined Data Freq.	Combined Data Percent
Weak	66	28.82	73	24.25	139	26.23
Medium	67	29.26	116	38.54	183	34.53
Strong	96	41.92	112	37.21	208	39.25
Totals	229	100	301	100	530	100

The data come only from X CDFI and the results of loan default in this sample may not be indicative of the more general small business market. The following table outlines the borrower, loan, lender and macroeconomic variables from this dataset.

Table 7. *Description of Independent Variables*

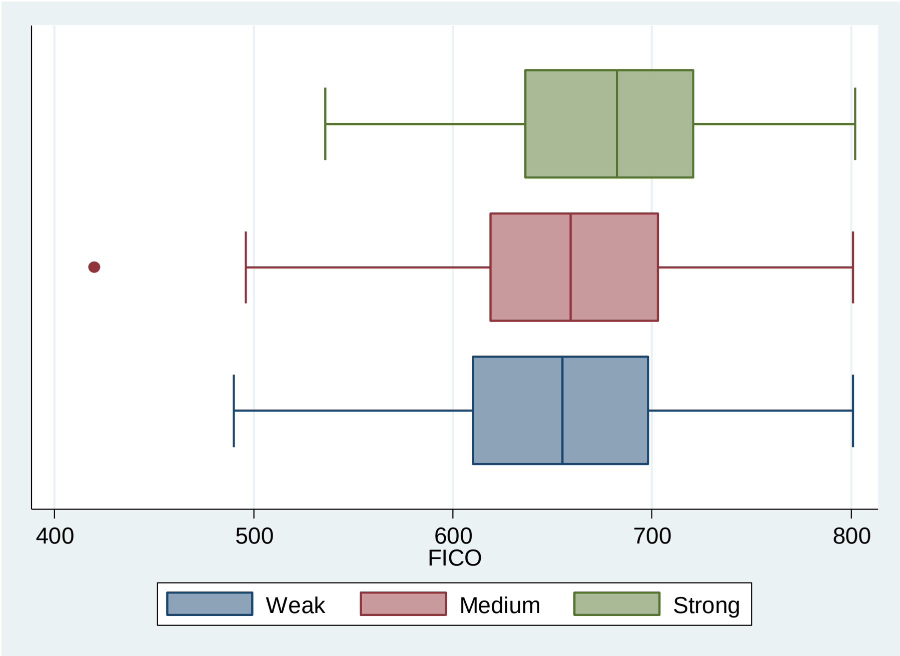
	Indep Var	Code	Units	Notes
Borrower-Specific	Management Experience	EXPMAN	Continuous	Number of years with management experience
	Female Borrower	FEMALE	*Dummy*: Female 1, Male 0	
	Personal FICO Score	FICO_10	Continuous	Three digit FICO score divided by 10 pts
	Industry Code	IND_AGG	Categorical	Derived from NAISCs codes
	Length of Business	LENGTHBUS	Continuous	Length of business in years
	Minority Borrower	MINORITY	*Dummy*: Minority 1, White 0	The minority variable combines African American, Asian, Hispanic and "Other"
	Debt to Income	DI	Continuous	The borrower's debt-to-income before the loan
	Start-up Business	STARTUP	*Dummy*: Start Up 1, Existing Business 0	Calculated using Length of Business. Start-up defined as length business ≤ 1 year
Loan and Lender Specific	Loan Age	AGE(M)	Continuous	The number of months between the origination date and the maturity date. If the loan is still active as of Oct 2009, 10/31/09 is used as the end date.
	Guarantee Percentage	GUAR_10	0, 5.0, 7.5, 8.5	SBA 0, and three options for SBA: 50, 75, and 85% (the interest rate percentage is divided by 10 units)

	Interest Rate Deviation from Prime	IntDevFromPr	Continuous	Calculated by subtracting interest rate[10] from the Federal Prime rate
	Log of the loan amount	LN(LAMT)	Continuous	
	Matured Loan	MATURED	*Dummy*: Matured 1, Active 0	
	SBA Loan	SBA	*Dummy*: SBA 1, non-SBA 0	
	Variable Interest Rate	VARINT	*Dummy*: Variable Rate 1, Fixed 0	
Macroeconomic	S&P 500	S&P_Orig	Continuous	The market value of the S&P 500 on day of origination
	Peak Change in Local Unemployment	UR_DevOrig	Continuous	Difference between unemployment at the origination day and the peak local unemployment rate over the life of the loan
Interaction	Int. Deviation from Prime x S&P 500	INTDEVx SP500	Continuous	Interaction term between the interest rate and S&P 500 at origination
	Variable Rate x S&P 500	VARINTx SP500	Continuous	Interaction term between variable interest rate and S&P 500 at origination

Before going into the empirical specification, some parts of dataset require additional attention. The literature states that in general, the borrower's FICO score is one of the most predictive measures of loan repayment. In the following graph, the values of "strong," "medium," and "weak" were assigned as of October 2009.

[10] The interest data are available as follows: if the loan matured, the interest rate is that at maturity. If the loan is active, the interest rate is that at 10/31/2009. *If the loan is fixed (the rate does not change over the course of the loan), the deviation from prime calculates the deviation between the fixed rate and the Fed Prime rate at origination. If the rate is variable, it calculates the variable rate at maturity (or at 10/31/2009 if active) and the Federal Reserve Prime rate at maturity (or at 10/31/2009). This is an important distinction, because most variable interest rates are calculated by X CDFI as the prime rate plus the spread. Thus for variable rates, the interest rate deviation from prime is the spread. The interpretation of this variable is the relative interest rate cost for this borrower compared to other rates he or she could find on the market.*

Figure 2. *Better FICO scores are mildly predictive of loan repayment as of October 2009*

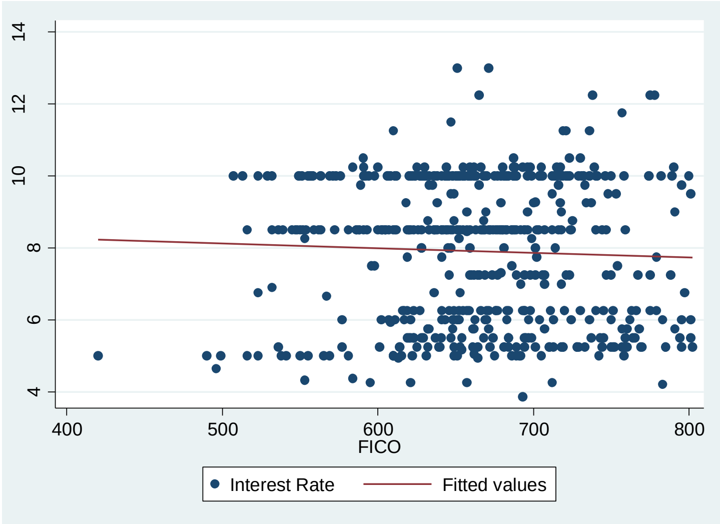


As shown in *Figure 2*, if the CDFI wanted to create a cut-off of 650 for loan applicants, this would capture both a high number of strong *and* weak loans. This box plot suggests that many other factors influence default, and even the historically most predictive factor, FICO score, does not alone adequately explain a significant portion of the loan strength.

CDFIs have access to two financial sources that are often not available to traditional banks: grants and subsidies. *Grants* are a source of revenue that the bank does not have to repay. *Subsidies*, in this paper, are defined as loans with subsidized interest rates – interest rates below market rates. Although these subsidized loans will have to be repaid, they are cheaper than the ones a bank would find on the market. X has access to investor grants, government guarantees, or other borrowing methods with interest rates below the market rate. X, however, does not always entirely pass along these below market interest rates to its borrowers, because it needs use some of the revenue to finance its internal underwriting costs.[11]

[11] This may bring up the question of X's profitability, but profitability is out of scope for this research paper.

Figure 3. *Borrowers with better FICO scores pay lower interest rates*



On average, borrowers with higher (better) FICO scores pay lower (cheaper) interest rates on their loans (*correlation,* ρ= -0.042). The scatter plot also shows some clumping, particularly around 10% and above 8%. These clusters are due to X's obliged interest rates for their program-based (investor-backed) loans. As discussed in the theoretical section, when interest rates are program-based, they can make good borrowers seem bad and *vice versa*. The dataset lacks program identifiers, and I will only be able to control for the known interest rates. Another way to look at the origination interest rate is to see how much it deviates from the Federal Prime rate.

Figure 4. *Some CDFI borrowers pay below Fed Prime interest rates*

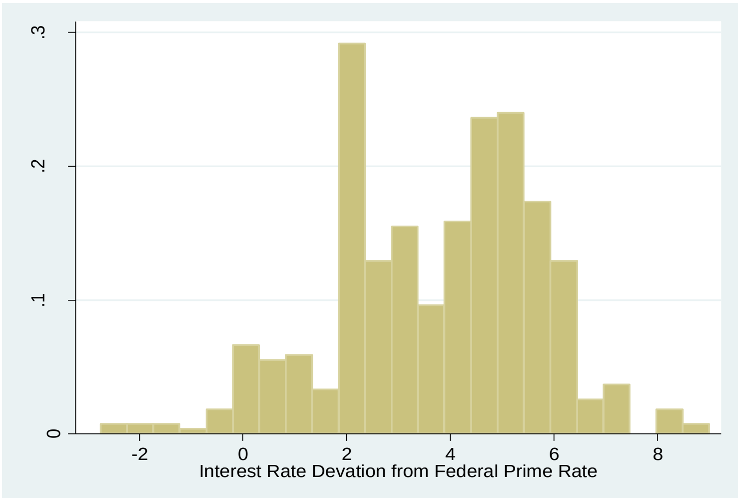
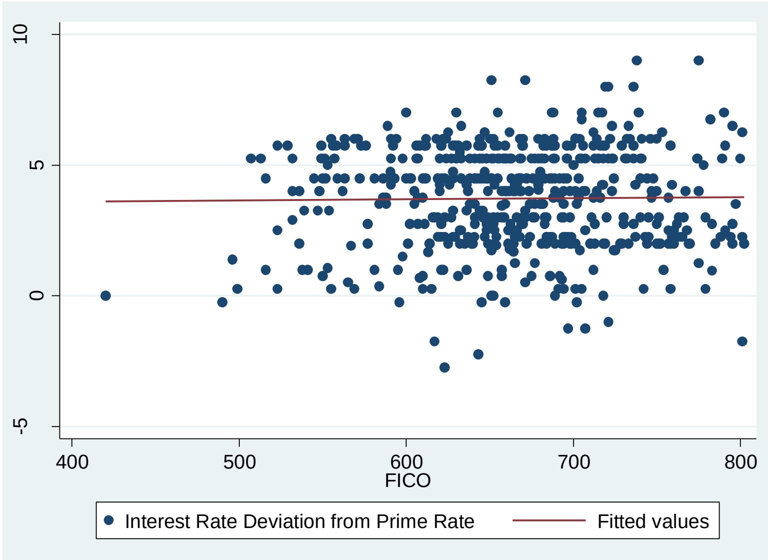


Figure 5. *The interest rate deviation from the Fed Prime rate holds relatively constant across FICO scores*



In *Figure 4*, a value of 0 on the x-axis indicates that the interest rate on the loan and the Federal Prime rate are the same. Some of the borrowers in this dataset actually pay interest rates that are cheaper than the Fed rate (*Figure 5*, ρ=0.014). This is possible because CDFIs are able to pass along selectively some of their subsidized rates to some of their borrowers. The most significant limitation with the interest rate data are that some of the variable rates are not calculated using *Fed Prime + Spread*. A few of the variables rates also do not update monthly (see footnote 10 for how the deviation rate is calculated and its assumptions). In addition, the monthly payments for some borrower do not change with the variable rate, and they only pay more at the end of the loan's life. If this occurs, they may not be affected by the changing Fed Rate. Future iterations of this model would have to include more complete interest rate data.

The small business loan industries are aggregated using NAICS codes. These variables can be used as controls to minimize the bias of one industry performing better in a period than another. The frequency and descriptive chart of the industry classifications is below.

Table 8. *Most of the loans are given to retail, recreation, or educational services*

Ind. Code	**NAICS Codes**	**General Name**	**Freq.**	**Percent**	***% Weak***
0		No code available	2	0.38	*0.00*
1	11	Farming	8	1.51	*37.50*
2	21, 22, 23	Mining, Utilities, Construction	30	5.66	*30.00*
3	31, 32, 33	Manufacturing	30	5.66	*33.33*
4	42, 44, 45, 48, 49	Wholesale, Retail Trade, Transportation and Warehousing	118	22.26	*33.05*
5	51, 52, 53, 54, 55, 56	Professional, Scientific, Technical Services, Real Estate, Finance, Insurance, Waste Management and Remediation Services	87	16.42	*26.44*
6	61, 62, 9	Educational Services, Health Care and Social Assistance, and Public Administration	105	19.81	*13.33*
7	71, 72	Arts, Entertainment, Recreation, Accommodation and Food Services	97	18.30	*31.96*
8	81	Automotive Repair, Machine and Equipment Repair, and Personal Care	53	10.00	*18.87*
Total			***530***	***100***	

SBLs can be particularly difficult to obtain from a traditional bank, especially if the company is a start-up. A start-up is defined a firm in business for one year or less.

Figure 6. *Most of the loans are for young businesses and start-ups*

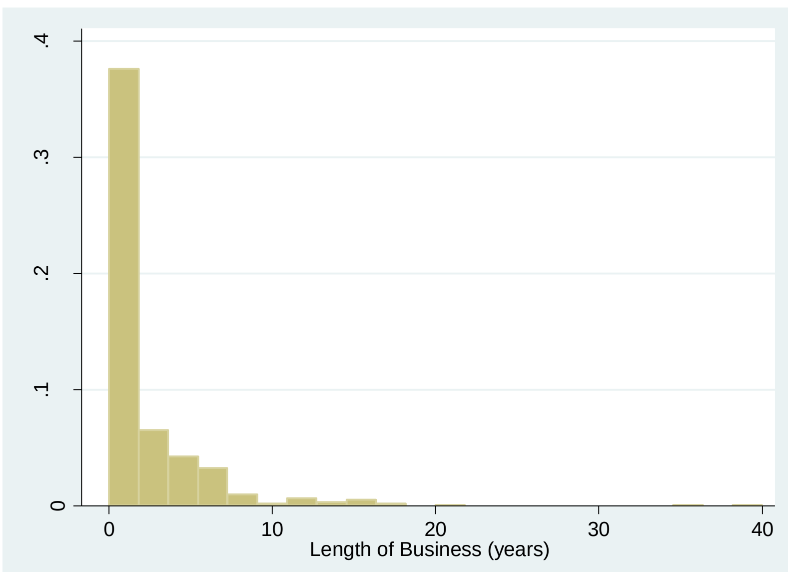


Table 9. *Length of business frequency distribution*

Years	Freq.	Percent	Cum.
0	272	54.08	54.08
1	72	14.31	68.39
2	32	6.36	74.75
3	28	5.57	80.32
4	25	4.97	85.29
5	14	2.78	88.07
6	14	2.78	90.85
7	16	3.18	94.04
8	7	1.39	95.43
9	2	0.4	95.83
10	2	0.4	96.22
11	1	0.2	96.42
12	5	0.99	97.42
13	1	0.2	97.61
14	2	0.4	98.01
16	5	0.99	99.01
17	2	0.4	99.4
20	1	0.2	99.6
36	1	0.2	99.8
40	1	0.2	100
Total	**503**	**100**	

Most of the loans in the dataset are below $50,000. In the literature, loans below $35,000 are considered to be "microloans." Small loans are especially expensive to service because the underwriting and administrative costs are high compared to the profits received per loan.

Table 10. *Loan amount by program*

	SBA Loans		**non-SBA Loans**		**Combined Data**	
Loan Size	Freq.	Percent	Freq.	Percent	Freq.	Percent
≤ $35k	64	27.95	249	82.72	313	59.06
$36k-50k	43	18.78	12	3.99	55	10.38
$50k-100	87	37.99	23	7.64	110	20.75
$101k+	35	15.28	17	5.65	52	9.81
Total	229	100	301	100	530	100

As noted earlier, CDFIs make an effort to extend loans to women, minorities, and low-wealth individuals. Of the 530 loans, 479 contain information about the race of the borrower. Due to the lack of observations, African American, Hispanic, Asian, and other are combined into a "minority" dummy variable.

Table 11. *Race frequency distribution by program*

	SBA Loans		**non-SBA Loans**		**Combined Data**	
Race	Freq.	Percent	Freq.	Percent	Freq.	Percent
African American	55	24.77	91	35.41	146	30.48
Hispanic	7	3.15	27	10.51	34	7.1
Asian	3	1.35	4	1.56	7	1.46
White	153	68.92	128	49.81	281	58.66
Other	4	1.8	7	2.72	11	2.3
Total	***222***	***100***	***257***	***100***	***479***	***100***

The number of government-guaranteed SBA loans given to women is almost exactly equal to men. The non-SBA loans are more commonly given to men, but it also rounds to approximately half.

Table 12. *Female frequency distribution by loan program*

	SBA Loans		**non-SBA Loans**		**Combined Data**	
Gender	Freq.	Percent	Freq.	Percent	Freq.	Percent
Male	115	50.22	162	53.82	277	52.26
Female	114	49.78	139	46.18	253	47.47
Total	***229***	***100***	***301***	***100***	***530***	***100***

The data in this paper were collected though a non-random sample. This dataset includes all of the weak loans in the CDFI's portfolio and may not include all of the strong loans. I do not know what percentage of weak/strong loans this sample contains compared to the population at large, so I cannot reweight my results to control for the non-random sample selection. I had to assume that this is relatively close to the actual population, and in the future, X would want to re-run these models when they have the time to collect all of the loan file data digitally.

Another weakness in the dataset is that the collection period is limited. The sample does not contain data on loans before 2002 or after 2007. This means the models not capture loan performance before the technology bubble in 2001 or during the current crisis, which started in 2008. The data also do not contain any information regarding the borrower's ability to obtain any other loans, both from CDFIs or traditional loans. In addition, the dataset lacks information on the corporate structure of the business (e.g., corporation, partnerships or sole proprietorships).

The dataset in this paper is only from the portfolio from X. Neither I nor X have been able to access loan-level data from any other CDFI, and, thus, the results from this paper cannot be compared with CDFIs across the country. The data also do not include any "shocks" to the borrower or business. Divorce, death in the family, or another major change in the life of a small business owner could affect his or her ability to repay the loan. The data also do not include loans that were denied – and X does not keep track of those loans in their digital database. This means this paper is unable to quantify any "gains" they could have made using the proposed credit-scoring model.

Furthermore, the data do not differentiate between new loans and renewals. Having a high level of renewals can be a serious problem in the dataset – especially if the renewal is paying off the original loan. After discussing this matter with X, they said that they only give around five renewal loans or fewer each year. They also said it would be difficult to identify the renewal loans in the dataset because their all of the information is contained in hard-copy files. Considering its rarity and the difficulty to isolate these renewal loans, I have not made any corrections for this in my data.

Co-borrowers also could be a problem in the data. Unfortunately, X only tracks one name per loan and the dataset does not have information on co-borrowers. This information exists also in the hard-copy files, which would again involve a manual tabulation. If there is a co-borrower it is often the owner and the business that have their names on the loan. In addition, I do not have any geographically identifying information, such as zip codes, for the loans, which could improve the results.

The biggest flaw in this dataset is the creation of the dependent variable. The strong, medium, weak designations are absorptive states. All loans start out as strong and once a loan becomes medium, it can never go back to strong. Because the data are not time dependent, I do not know at what time a loan started to be in arrears. This is an important distinction, because a loan that defaults in month 1 is much worse than a loan that defaults in the last month. A bank would prefer to recoup 99% of a loan than only 5%. However, in this dataset, both of those loans would be classified as weak.

Because I do not know when a loan starts to go bad, I cannot state with certainty that any of the macroeconomic variables affected its late payments. For example, I know the origination dates and the expected date of maturity for each loan. The average and peak unemployment variables are calculated using this estimated life of the loan (or if the loan had not matured by October 2009, 10/31/09 is selected as the "end date"). For instance, if loan Z originated in Feb 2002 and had a maturity date of Dec 2008 and the peak unemployment was 8.1% in late 2008, but the loan started to become delinquent in 2007, the relationship between the peak local unemployment and the loan strength would be deceiving. One solution to this would be to develop a hazard model approach and a corresponding dataset measures the influence of time on borrower default.

V. Empirical Specification

Because the dependent variable in this dataset has three outcomes, this provides an opportunity to run three separate regressions. This section discusses the results from two binary models, (**1**) comparing “strong” loans to “weak and medium” loans – a *Strong/Not Strong Model*, and (**2**) a binary model comparing “weak” loans to “strong and medium” – a *Weak/Not Weak Model*. The results from (**3**) a multinomial logistic regression with all three dependent variable outcomes – strong, medium, and weak – are included in *Appendix A*.

These models are run on *all loans* in the portfolio and then on two sub-populations: *start-up loans* and *microloans*.

All Loans, Strong/Not Strong

The dependent variable is equal to 1 if the loan is classified as “strong” and 0 if it is “medium” or “weak.” The independent variables in the regression are presented in the same order as Table 7 on pg. 22, which also includes their descriptions and units. The four categories, (1) borrower, (2) loan, (3) lender, and (4) macroeconomic remain the same, except due to a lack of available lender information in this dataset, the loan and lender characteristics are combined.

The selected borrower variables include (i) prior owner management experience, (ii) a female dummy variable, (iii) the FICO score, (iv) the number of years in the business, (v) a minority dummy variable, and (vi) the debt-to-income *before* taking on X’s loan. The minority dummy variable is equal to 1 if the borrower is “African American,” “Asian,” “Hispanic” or “other.”[12] These borrower-specific characteristics are shaded in blue in *Regression Table 1.1*.

[12] The number of observations of Asian, Hispanics and “other” were not enough to warrant individual dummy variables.

The selected loan and lender variables include: (i) the age of the loan in months, (ii) the government guarantee percentage of each individual loan, (iii) the deviation of each loan's interest rate from the Fed Prime rate, (iv) the natural log of the loan amount, (v) a dummy variable for whether or not the loan has matured, and (vi) a dummy for whether the loan's interest rate is variable or fixed.

The two macroeconomic variables are (i) the market value of the S&P 500 on the day of origination, and (ii) the peak change in the local unemployment rate over the life of the loan. The first value captures the over-all economic health on the day the loan originates. The second economic variable is more specific to the loan. The peaks in the cycle are probably more challenging for SBL solvency than the average value over the life of the loan (which smoothes out the peaks). In addition, local unemployment rates are less volatile than other economic indications, such as the S&P 500.

Finally, because the types of loans change with the economic health of the population, the regression includes interaction terms. The overall economic climate likely affects the bank's assigned interest rate and whether or not the borrower gets a variable rate. The interaction terms are (i) a combination of the interest rate deviation from prime and the S&P 500 value at origination and (ii) a combination of the variable interest rate dummy and S&P 500 at origination. In this dataset, more variable rate loans originate when the economy is strong. The interaction terms help isolate defaults due to loan characteristics, macro-characteristics or when the macro-variables influence the loan variables and the combined effect of this on a loan.

The *Strong/Not Strong* model includes five (5) regressions, which are outlined in *Regression Table 1.1* on *pg. 36.* The first four regressions use OLS, which has coefficients that are easier to interpret and more straightforward for credit-scoring. The last regression binds the dependent variable values between 1 and 0, and the coefficients are odds ratios from the logit regression. When regressing *Strong/Not Strong* on borrower characteristics, only FICO is significant in model (1). With each 10 point increase in FICO score, the probability of repayment increased by 1.4%.

After adding loan and macroeconomic controls in regression (2), matured loans are 17% less likely to be strong. This makes sense given the absorptive nature of the dependent variable. A loan that becomes weak can never go back to strong. With 95% significance, for each 1% increase in the peak unemployment rate, the loan has a 4% chance *less* likely of being strong. Sharp peaks of the local unemployment rate burden small businesses.

There are two surprising results in this regression (2). First, it indicates that loans with greater deviations from Fed Prime (more expensive loans) are more likely to be strong. In addition, variable rate loans are 25% more likely to be strong. The literature would expect the opposite sign for both of these variables. This occurs because both of these variables are also highly correlated with the macroeconomic variables at origination. Using interaction terms isolates these effects. The interaction terms in regression (3) remove the bias in variable interest rate and interest deviation from prime. They are now both negative values (expected) and not significant. The interaction term provides a control for the combined effect of a variable interest rate given in a strong economy.

In addition in regression (3), loans given during strong climates are more likely to be weak – perhaps indicating that the CDFI has weaker criteria for their borrowers or weaker borrowers looked stronger during good business cycles. However, if the economy experienced a large change in unemployment during the life of the loan, the borrower is much more likely to default. For each 1% increase in local unemployment, the probability of being strong decreases by 4% (90% confidence), which is the same result in regression (2).

Regression (4) includes industry controls. Even though none of the individual industry dummies are significant, they still control for unexplained factors in the regression. It is encouraging to find that most of the values remain the same as (3). The one difference is that S&P 500 at origination is no longer significant. Of note, even regression (4) only has an R^2 of 12.6%. This means that even in the most complete regression, *very little* of the repayment variation is explained by conventional variables.

One beneficial way to interpret the logit results is to create an odds ratio table, which is displayed in column (5). The variables that are significant in the logit regression are also the same level of significance in the displayed odds ratios. The benefit of an odds ratio table is that the ratios show the relative importance of each variable (much like the OLS coefficients). For example, for each 10 unit increase in FICO score, the odds ratio of having a strong loan increases by 6.7%.

This model displays most of the same results as the OLS regression, with a few exceptions. The odds ratio model indicates loans with large interest rate deviations from the Federal Reserve rate are more likely to be weak. This makes sense because expensive loans are likely harder to pay-off. Significant at the 95% level, for each 10 point increase in the S&P 500 at origination, the odds of being a strong loan decreases by 5%. This is weakly significant in regression (3) and not significant in (4). This echoes the same reasoning as the OLS regression: either loans given in strong periods have weaker selection criteria or weak borrowers can seem stronger during these strong economic cycles.

Regression 1.1 All Loans *[Dependent Variable: Strong=1, Not Strong=0]*

	VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry controls*	(5) Logistic *Odds Ratios*
Borrower-Specific Variables	Management Exp. *(yrs)*	0.002	0.002	0.002	0.001	1.009
		(0.003)	(0.003)	(0.003)	(0.003)	(0.015)
	Female *(dummy)*	-0.010	0.017	0.017	-0.004	1.069
		(0.046)	(0.047)	(0.046)	(0.048)	(0.232)
	FICO	0.014***	0.013***	0.013***	0.014***	1.061***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.020)
	Length Business *(yrs.)*	0.008	0.005	0.006	0.006	1.025
		(0.006)	(0.006)	(0.006)	(0.006)	(0.027)
	Minority *(dummy)*	-0.059	-0.041	-0.044	-0.059	0.833
		(0.048)	(0.048)	(0.047)	(0.049)	(0.187)
	Debt-to-income	-0.004	-0.002	-0.003	0.000	0.948
		(0.014)	(0.014)	(0.014)	(0.014)	(0.155)
Loan and Lender Specific	Age of loan *(months)*		-0.002	-0.003	-0.004	0.991
			(0.002)	(0.002)	(0.002)	(0.011)
	Gov't Guar. %		-0.013	-0.011	-0.010	0.946
			(0.009)	(0.009)	(0.010)	(0.043)
	Int Deviation from Prime		0.027**	-0.132	-0.100	0.402**
			(0.013)	(0.081)	(0.082)	(0.183)
	Ln(Loan Amount)		0.012	0.023	0.026	1.129
			(0.035)	(0.035)	(0.036)	(0.186)
	Matured *(dummy)*		-0.169*	-0.182*	-0.178*	0.408*
			(0.096)	(0.096)	(0.099)	(0.205)
	Variable Rate *(dummy)*		0.247***	-0.231	-0.074	0.075
			(0.067)	(0.373)	(0.382)	(0.154)
Macro	S&P 500 at origination		-0.000	-0.007*	-0.006	0.949**
			(0.002)	(0.004)	(0.004)	(0.021)
	Peak Δ Local Unemp. Rate		-0.040**	-0.040*	-0.037*	0.798**
			(0.020)	(0.021)	(0.021)	(0.085)
	Interest Dev*S&P 500			0.001*	0.001*	1.009**
				(0.001)	(0.001)	(0.004)
	Variable Rate*S&P 500			0.004	0.002	1.033*
				(0.003)	(0.003)	(0.019)
	Constant	-0.518**	-0.434	0.270	0.168	
		(0.252)	(0.498)	(0.590)	(0.688)	
	Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
	Observations	443	443	443	443	443
	R-squared	0.045	0.099	0.110	0.126	*LR* $\chi^2(16)=54.1$
	Adj. R-squared	0.032	0.069	0.076	0.076	*Prob>*χ^2 = 0.00

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

All Loans, Weak/Not Weak

The second model, *Regression Table 1.2*, uses a *Weak/Not Weak* dependent variable. If the loan is "weak" it is given a value of 1. If it is "strong" or "medium" it is given a value of 0. In this regression, more of the borrower-only characteristics are influential in predicting the likelihood of repayment. With each additional year of management experience, a borrower is 0.6% less likely to have a weak loan (90% confidence). Management experience is different from length of business. A borrower could have management experience in other companies. The length of business indicates how many years the firm has been in business at the day of origination. With each additional year of a business's life, the probability of being a "weak" loan decreases by 1.6% (99% confidence).

Regression (2) marks the first time the gender variable becomes significant in this paper. When macro effects are included, female borrowers are 7.2% *less likely* to own weak loans. This finding reflects the idea that "female borrowers are better borrowers" – a slogan that is often used in the developing world microfinance communities.

In regression (3), with each 1% increase in the peak unemployment, the loan is 5.7% *more likely* to be weak (99% confidence), again reflecting that sharp peaks in unemployment from the origination unemployment are difficult for a business to overcome. With each 10% increase in government guarantee, the probability of default also increases by 3.5% (99% confidence). This is an expected sign because the bank probably planned to have a higher government backing on a riskier loan. This also may indicate a moral hazard problem, if the bank lacks a vested interest in modifying the loan if it knows it will recoup some of the loss through the guarantee. However, this is probably less likely because the bank has to prove that it tried to collect the loan to get the government/investor funding.

In addition, with each 1% increase in the interest rate deviation from prime (e.g. a more expensive loan), the loan is 16% *more likely* to be weak. Although the sign is expected, this is a surprisingly large effect and likely depends on the investor-assigned program-based interest rates. However, given the ambiguity of the variable-rate data, this may not be the true size. The counterintuitive negative sign on the variable interest rate dummy in (2) has now become somewhat more conventional in (3), because interaction terms remove the bias of variable rates given in strong economic climates. Regression (3) states that a variable interest rate loan is 59% more likely to be weak (90% confidence). Although the sign is expected, the magnitude is large.

Although none of the industry dummies are individually significant, when industry controls are included (4), most of the results stay the same with one exception: the variable rate is no longer significant. The R^2 in (4) of the *Weak/Not Weak* regression is 27%, and is much better than in the *Strong/Not Strong* (4), which is 7.6%, but these conventional variables still explain little of the overall variation. This is because default often occurs due to unobserved characteristics, such as a crisis in the personal life of the small business owner or shocks in the cost structure of the small business.

The final column (5) displays the odds ratios. With each year increase in the business, the loan has 13% lower odds of being weak. With each 10 point increase in FICO, the odds of being weak also decrease by 9%. Each 10% increase in government guarantee increases the odds of a weak loan by 34%. This could again reflect that the bank is willing to take on a riskier borrower only if there is some government guarantee. The odds ratio results are comparable to the OLS regression, except that in the odds ratios, it indicates with more significance that women are *less likely* to hold weak loans than men – women have a 46% lower odds of holding a weak loan.

The multinomial logistic regression for *all loans* is discussed in **Appendix A**.

Regression 1.2 All Loans *[Dependent Variable: Weak=1, Not Weak=0]*

	VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry controls*	(5) Logistic *Odds Ratios*
Borrower-Specific Variables	Management Exp. *(yrs)*	-0.006**	-0.005*	-0.006**	-0.005*	0.962*
		(0.003)	(0.003)	(0.003)	(0.003)	(0.020)
	Female *(dummy)*	-0.058	-0.072*	-0.075*	-0.056	0.537**
		(0.042)	(0.039)	(0.039)	(0.040)	(0.146)
	FICO	-0.009***	-0.012***	-0.012***	-0.013***	0.912***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.022)
	Length Business *(yrs.)*	-0.016***	-0.011**	-0.011**	-0.011**	0.866***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.048)
	Minority *(dummy)*	0.060	0.037	0.038	0.057	1.372
		(0.043)	(0.040)	(0.040)	(0.041)	(0.365)
	Debt-to-income	-0.015	-0.018	-0.017	-0.020*	0.879
		(0.013)	(0.012)	(0.012)	(0.012)	(0.119)
Loan and Lender Specific	Age of loan *(months)*		0.003	0.001	0.002	1.018
			(0.002)	(0.002)	(0.002)	(0.014)
	Gov't Guar. %		0.038***	0.035***	0.033***	1.344***
			(0.008)	(0.008)	(0.008)	(0.093)
	Int Deviation from Prime		0.001	0.166**	0.131*	3.563**
			(0.011)	(0.068)	(0.069)	(2.099)
	Ln(Loan Amount)		0.014	0.000	-0.000	0.910
			(0.029)	(0.029)	(0.030)	(0.190)
	Matured *(dummy)*		0.151*	0.166**	0.146*	3.192**
			(0.082)	(0.081)	(0.082)	(1.624)
	Variable Rate *(dummy)*		-0.470***	0.591*	0.454	8.845
			(0.057)	(0.312)	(0.318)	(20.681)
Macro	S&P 500 at origination		-0.000	0.009***	0.007**	1.070**
			(0.002)	(0.003)	(0.003)	(0.031)
	Peak Δ Local Unemp. Rate		0.051***	0.057***	0.055***	1.385***
			(0.017)	(0.017)	(0.018)	(0.152)
	Interest Dev*S&P 500			-0.001**	-0.001**	0.989**
				(0.001)	(0.001)	(0.005)
	Variable Rate*S&P 500			-0.009***	-0.008***	0.955**
				(0.003)	(0.003)	(0.019)
	Constant	0.960***	0.768*	-0.104	-0.005*	
		(0.229)	(0.422)	(0.493)	(0.003)	
	Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
	Observations	443	443	443	443	443
	R-squared	0.061	0.227	0.255	0.274	*LR* $\chi^2(16)=131$
	Adj. R-squared	0.048	0.201	0.227	0.233	*Prob*$>\chi^2 = 0.00$

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

Start-Up Loans, Strong/Not Strong

The CDFI data has two important sub-groups that should be looked at separately: (1) start-up loans and (2) microloans. Start-up loans are businesses that have been in business for a year or less. The *Strong/Not Strong* start-up loan regressions are displayed in *Regression 2.1*. The five regressions on the start-up loans are similar to the outputs on the all-loans model. This section highlights the differences.

In general, high FICO scores have more of an impact on loan strength in start-up loans than in the all-loans model. Comparing (4), in start-up loans a 10 point increase in FICO increases the probability of a strong loan by 1.7% compared to 1.4% in the all-loans regression. Although the interest rate deviation from prime is significant in the all-loans model, it is not significant in the start-up loan model. This could mean that start-up borrowers are not as sensitive to interest rates as borrowers on the whole. Although this may sound surprising, perhaps it is because the entire population includes micro-borrowers and other types of borrowers, who could be much more sensitive to interest rate deviations.

In the logistic regression, variable-rate loans are significantly more likely to be weak for start-up loans. The all-loans analysis does not find this result. This suggests that start-up borrowers have more difficulty paying off variable interest rates than other borrowers. Finally, start-up borrowers are more sensitive to peak changes in the local unemployment rate. Comparing (4), for each 1% change in the peak rate, start-up borrowers are 4.8% more likely to default, compared to 3.7% for all loans.

Regression 2.1 Start-up Loans *[Dependent Variable: Strong=1, Not Strong=0]*

VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry Controls*	(5) Logistic *Odds Ratios*
Management Exp. *(yrs)*	0.001	-0.000	0.000	0.001	1.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.019)
Female *(dummy)*	-0.008	0.027	0.030	0.001	1.146
	(0.055)	(0.056)	(0.056)	(0.056)	(0.310)
FICO	0.014***	0.016***	0.016***	0.017***	1.079***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.025)
Length Business *(yrs.)*	-0.047	-0.039	-0.036	-0.017	0.813
	(0.068)	(0.069)	(0.069)	(0.070)	(0.281)
Minority *(dummy)*	-0.077	-0.064	-0.065	-0.068	0.741
	(0.057)	(0.057)	(0.057)	(0.057)	(0.210)
Debt-to-income	-0.003	-0.002	-0.002	0.001	0.921
	(0.014)	(0.014)	(0.014)	(0.014)	(0.238)
Age of loan *(months)*		-0.002	-0.001	-0.003	0.999
		(0.002)	(0.003)	(0.003)	(0.014)
Gov't Guar. %		-0.018	-0.013	-0.011	0.930
		(0.012)	(0.012)	(0.012)	(0.056)
Int Deviation from Prime		0.014	-0.105	-0.055	0.399
		(0.016)	(0.094)	(0.095)	(0.229)
Ln(Loan Amount)		0.007	0.014	0.016	1.066
		(0.043)	(0.043)	(0.045)	(0.226)
Matured *(dummy)*		-0.223**	-0.220**	-0.226**	0.308*
		(0.111)	(0.111)	(0.113)	(0.193)
Variable Rate *(dummy)*		0.301***	-0.392	-0.220	0.013*
		(0.078)	(0.434)	(0.437)	(0.035)
S&P 500 at origination		-0.002	-0.008*	-0.007	0.937**
		(0.003)	(0.004)	(0.004)	(0.027)
Peak Δ Local Unemp. Rate		-0.048**	-0.051**	-0.048**	0.719**
		(0.023)	(0.023)	(0.024)	(0.097)
Interest Dev*S&P 500			0.001	0.001	1.009*
			(0.001)	(0.001)	(0.005)
Variable Rate*S&P 500			0.006	0.004	1.053**
			(0.004)	(0.004)	(0.025)
Constant	-0.566*	-0.322	0.319	0.319	
	(0.306)	(0.598)	(0.709)	(0.709)	
Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
Observations	309	309	309	309	309
R-squared	0.053	0.123	0.134	0.134	*LR* $\chi^2(16)=48.4$
Adj. R-squared	0.034	0.081	0.086	0.086	*Prob*$>\chi^2$ *= 0.00*

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

Start-Up Loans, Weak/Not Weak

In the *Weak/Not Weak* model in *Regression 2.2* for start-up loans had similar results as the all loans regression. The following section highlights the differences.

Management experience is significant in predicting default for all-loans, but it is *not* significant for predicting default in start-up loans. Although the start-up borrowers in general have less experience than the all-loan borrowers in the data, this does not explain entirely why it is not significant. It is a surprising result, because the literature suggests that start-ups fare better if the founder has more work experience.

Additionally, the length of the business (in years) is highly significant for all-loans, and intuitively, the length of business is *not* significant for the start-up loans – because by definition, start-up loans are those in business for a year or less. The rest of the numbers in start-up model are comparable to the all loans model.

The relative risk ratio for the multinomial logistic regression for *start-up loans* is discussed in **Appendix A**.

Regression 2.2 Start-Up Loans *[Dependent Variable: Weak=1, Not Weak=0]*

VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry Controls*	(5) Logistic *Odds Ratios*
Management Exp. *(yrs)*	-0.006	-0.003	-0.004	-0.003	0.972
	(0.004)	(0.004)	(0.004)	(0.004)	(0.022)
Female *(dummy)*	-0.065	-0.090*	-0.094*	-0.074	0.540**
	(0.053)	(0.050)	(0.050)	(0.051)	(0.167)
FICO	-0.011**	-0.016***	-0.015***	-0.016***	0.913***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.024)
Length Business *(yrs.)*	0.026	0.028	0.024	0.005	1.075
	(0.065)	(0.062)	(0.062)	(0.064)	(0.385)
Minority *(dummy)*	0.061	0.045	0.045	0.051	1.296
	(0.055)	(0.051)	(0.051)	(0.052)	(0.394)
Debt-to-income	-0.016	-0.017	-0.016	-0.019	0.889
	(0.014)	(0.013)	(0.013)	(0.013)	(0.126)
Age of loan *(months)*		0.001	0.000	-0.000	1.006
		(0.002)	(0.002)	(0.003)	(0.016)
Gov't Guar. %		0.041***	0.035***	0.031***	1.292***
		(0.011)	(0.011)	(0.011)	(0.105)
Int Deviation from Prime		0.003	0.121	0.085	2.847*
		(0.015)	(0.085)	(0.086)	(1.774)
Ln(Loan Amount)		0.036	0.030	0.040	1.124
		(0.039)	(0.039)	(0.040)	(0.279)
Matured *(dummy)*		0.198**	0.191*	0.174*	3.278**
		(0.101)	(0.100)	(0.102)	(1.924)
Variable Rate *(dummy)*		-0.520***	0.415	0.334	5.638
		(0.071)	(0.390)	(0.395)	(14.544)
S&P 500 at origination		0.002	0.009**	0.007*	1.066**
		(0.002)	(0.004)	(0.004)	(0.033)
Peak Δ Local Unemp. Rate		0.051**	0.057***	0.056***	1.355**
		(0.021)	(0.021)	(0.021)	(0.169)
Interest Dev*S&P 500			-0.001	-0.001	0.992
			(0.001)	(0.001)	(0.006)
Variable Rate*S&P 500			-0.008**	-0.007**	0.960*
			(0.003)	(0.003)	(0.021)
Constant	1.085***	0.586	-0.117	-0.003	
	(0.295)	(0.541)	(0.638)	(0.004)	
Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
Observations	309	309	309	309	309
R-squared	0.047	0.223	0.242	0.271	*LR* $\chi^2(16)=83.1$
Adj. R-squared	0.028	0.186	0.200	0.209	*Prob*$>\chi^2 = 0.00$

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

Microloans, Strong/Not Strong

Microloans are loans under $35,000, which is the industry standard cut-off point for microloans. Microloans are among the most expensive to service because the loan amounts and corresponding interest rates are often too small to offset the underwriting and servicing costs. Pre-approval systems or semi-automatic credit-scoring systems for microloans can help reduce these burdens. The microloan results for *Strong/Not Strong* are displayed in *Regression 3.1*. The regressions for the microloans are also similar to the all loans and start-up loans. The following section highlights the differences.

Microloan default is less influenced by FICO than start-up or all loans. With every 10 point increase in FICO, the probability of being a strong loan only increases by 1.2% for micro-borrowers, compared to 1.4% (all-loans) and 1.7% (start-up). This makes sense, because micro-borrowers are often not well represented (if represented at all) in national credit-scoring databases. Julie Gerschick (2002) echoes this finding, citing that many micro-borrowers often borrow from family members and pawnshops which often lack a credit bureau rating or report.

With each 10% increase in government guarantee, the microloans are *more likely* to be strong (model 5). This is a surprising result, because the expectation would be *less likely* to be strong. This suggests that these "good" micro-borrowers may be untraditional and have trouble finding funds for good business proposals unless they have government guarantees.

Micro-borrowers are also much more sensitive to deviations in the interest rate. For each 1% increase compared to the Fed Rate, micro-borrowers are 27% less likely to be strong. This large number, and likely explains why this shows up weakly in the all-loans model (which includes micro-borrowers) but not in the start-up loans (which does not include micro-borrowers).

Interestingly, loans given to micro-borrowers during strong economic climates are much more likely to default than loans given to start-up borrowers or borrowers in the all-loans model. With each 10 point increase in the S&P 500 at origination, micro-borrowers are 1.7% more likely to default compared to 0.6% (all loans) and 0.7% (start-up loans). This may suggest that underwriting criteria for micro-borrowers is more lenient in good business cycles, or that micro-borrowers appear to be stronger during these times.

The loan amount variable is not significant for all loans or start-up loans, but it does become weakly significant (90% confidence) for micro-borrowers. Micro-borrowers who took out larger loans are more likely to repay them.

Regression 3.1 Microloans (Loans under $35k) *[Dependent Variable: Strong=1, Not Strong=0]*

VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry Controls*	(5) Logistic *Odds Ratios*
Management Exp. *(yrs)*	0.000	0.001	0.000	0.000	1.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.021)
Female *(dummy)*	-0.028	0.014	-0.000	-0.018	1.024
	(0.061)	(0.064)	(0.064)	(0.066)	(0.310)
FICO	0.015***	0.013**	0.012**	0.012**	1.060**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.026)
Length Business *(yrs.)*	-0.004	-0.003	-0.003	-0.005	0.984
	(0.008)	(0.008)	(0.008)	(0.008)	(0.038)
Minority *(dummy)*	-0.082	-0.065	-0.075	-0.096	0.628
	(0.061)	(0.062)	(0.061)	(0.064)	(0.189)
Debt-to-income	-0.007	-0.004	-0.007	-0.006	0.497
	(0.014)	(0.015)	(0.015)	(0.015)	(0.313)
Age of loan *(months)*		-0.001	-0.002	-0.003	0.990
		(0.003)	(0.003)	(0.003)	(0.014)
Gov't Guar. %		0.020	0.070	0.062	1.461*
		(0.036)	(0.043)	(0.043)	(0.325)
Int Deviation from Prime		0.015	-0.329**	-0.270*	0.162**
		(0.022)	(0.154)	(0.159)	(0.129)
Ln(Loan Amount)		0.078	0.078	0.085*	1.526*
		(0.050)	(0.050)	(0.051)	(0.378)
Matured *(dummy)*		-0.180	-0.204	-0.210	0.303
		(0.169)	(0.168)	(0.171)	(0.296)
Variable Rate *(dummy)*		0.180	-1.960	-1.646	0.000*
		(0.190)	(1.238)	(1.270)	(0.000)
S&P 500 at origination		-0.002	-0.018**	-0.017**	0.904***
		(0.003)	(0.007)	(0.008)	(0.035)
Peak Δ Local Unemp. Rate		-0.057**	-0.047	-0.039	0.773
		(0.029)	(0.029)	(0.029)	(0.129)
Interest Dev*S&P 500			0.003**	0.003*	1.019**
			(0.001)	(0.001)	(0.008)
Variable Rate*S&P 500			0.014	0.011	1.080*
			(0.009)	(0.009)	(0.048)
Constant	-0.532*	-0.748	1.039	0.769	
	(0.322)	(0.614)	(0.980)	(1.027)	
Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
Observations	256	256	256	256	256
R-squared	0.054	0.096	0.116	0.136	*LR* $\chi^2(16)=34.3$
Adj. R-squared	0.031	0.043	0.057	0.046	*Prob*$>\chi^2 = 0.00$

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

Microloans, Weak/Not Weak

In *Regression 3.2*, the new dependent variable is *Weak/Not Weak* for microloans. The results in this section are also similar to the results for *Weak/Not Weak* in the start-up and all-loan models. The following section highlights the differences.

The micro-borrower *Weak/Not Weak* regressions mark the first time debt-to-income becomes significant. For each 0.01 increase in the debt-to-income ratio for a micro-borrower, the loan becomes 2.2% more likely to be weak. This variable is not significant in the all-loans and start-up loans models. This indicates that micro-borrowers who have more debt in their personal portfolios are more likely to default when taking out business debt (a microloan).

In contrast, the *Strong/Not Strong* microloan model suggests that borrowers who take on larger loans are more likely to repay. Combined, these models indicate that borrowers with lots of personal debt are *more likely* to default, but borrowers who take out larger debts for their business are *less likely* to default. Perhaps, the underlying reason is simply that micro-borrowers with high levels of pre-loan personal debt have a different type of character from borrowers from those who take out large microloans. In addition, because many of these micro-borrowers are not adequately represented in the consumer (FICO) credit bureaus, the borrowers with high levels of debt should have lower FICO scores. If the FICO scores correctly reflected this, perhaps the debt-to-income variable would not be significant. More analysis would need to be done to synthesize what these conflicting results mean.

Interestingly, government guarantees are *not* significant in predicting microloan default in model (4), even though these guarantees are significant for all-loans and start-up loans.[13] Perhaps the lack of significance on the guarantee variable, like in the *Strong/Not Strong* micro

[13] Of note, only 22% of the microloans have government guarantees.

analysis, indicates that micro-borrowers are unable to get loans elsewhere, even though they are strong borrowers, because they seem "risky." The higher government guarantees likely encourage the CDFI to extend credit to (good) borrowers that they might not normally want to underwrite. Therefore, the lack of significance on this variable could indicate that the guarantees are going to the "right" type of borrower – someone who is strong, but seems riskier by conventional measurements.

Management experience for micro-borrowers, like start-up borrowers, is not significant. In contrast, this is predictive for the all-loans data. Comparing the third models, female micro-borrowers are *much less likely* to be weak than men (11% less likely) than start-up females (9.4% less likely) and all loan females (7.5% less likely to be weak).

The interest variables in the microloan analysis need additional attention. The (4) model, with industry controls, indicates that with each 1% increase in deviation from Federal Prime, micro-lenders are 35% more likely to be weak compared to 16% (all loans) and not significant for start-up loans. In addition, variable-rate loans given to micro-borrowers are 221% more likely to be weak, compared to 59% (all loans) and not significant for start-up loans. Both of these numbers for micro-borrowers are extraordinarily large. In part, this could be because only 18% of microloans have variable rates, and of that 18%, 96% are SBA loans. Of the fixed rate loans, only 4% are SBA. If the SBA and non-SBA populations are significantly different, which they likely are, this could explain the large values on variable rate and interest rate deviation for the micro-borrowers. Perhaps SBA variable-rate loans default in micro-borrower populations at an exceptionally high rate.

The relative risk ratio for the multinomial logistic regression for *microloans* is discussed in **Appendix A**.

Regression 3.2 Microloans (Loans under $35k) *[Dependent Variable: Weak=1, Not Weak=0]*

VARIABLES	(1) OLS *Borrower-specific*	(2) OLS *Includes macro*	(3) OLS *Interaction terms incl.*	(4) OLS *Industry Controls*	(5) Logistic *Odds Ratios*
Management Exp. *(yrs)*	-0.005	-0.005	-0.005	-0.005	0.968
	(0.004)	(0.004)	(0.004)	(0.004)	(0.028)
Female *(dummy)*	-0.085	-0.129**	-0.110**	-0.107*	0.406**
	(0.056)	(0.056)	(0.055)	(0.057)	(0.147)
FICO	-0.016***	-0.017***	-0.016***	-0.017***	0.888***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.028)
Length Business *(yrs.)*	-0.013*	-0.015**	-0.015**	-0.015**	0.851**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.060)
Minority *(dummy)*	0.053	0.040	0.051	0.061	1.302
	(0.055)	(0.054)	(0.053)	(0.055)	(0.443)
Debt-to-income	-0.016	-0.025*	-0.022*	-0.022*	0.867
	(0.013)	(0.013)	(0.013)	(0.013)	(0.131)
Age of loan *(months)*		0.005*	0.005**	0.005*	1.042**
		(0.003)	(0.003)	(0.003)	(0.019)
Gov't Guar. %		0.060*	0.008	0.008	1.040
		(0.031)	(0.037)	(0.038)	(0.433)
Int Deviation from Prime		0.016	0.396***	0.351**	123.430***
		(0.019)	(0.134)	(0.138)	(209.413)
Ln(Loan Amount)		-0.033	-0.032	-0.034	0.889
		(0.044)	(0.043)	(0.044)	(0.253)
Matured *(dummy)*		0.096	0.126	0.129	3.232
		(0.149)	(0.146)	(0.148)	(2.658)
Variable Rate *(dummy)*		-0.607***	2.448**	2.206**	4.608e+13***
		(0.166)	(1.073)	(1.099)	(4.914e+14)
S&P 500 at origination		0.001	0.019***	0.017**	1.269***
		(0.003)	(0.006)	(0.007)	(0.107)
Peak Δ Local Unemp. Rate		0.057**	0.045*	0.042*	1.242
		(0.025)	(0.025)	(0.025)	(0.177)
Interest Dev*S&P 500			-0.004***	-0.003***	0.957***
			(0.001)	(0.001)	(0.015)
Variable Rate*S&P 500			-0.020***	-0.018**	0.777***
			(0.008)	(0.008)	(0.064)
Constant	1.371***	1.358**	-0.683	-0.307	
	(0.293)	(0.539)	(0.849)	(0.889)	
Industry Controls?	*No*	*No*	*No*	*Yes*	*No*
Observations	256	256	256	256	256
R-squared	0.083	0.187	0.223	0.243	*LR* $\chi^2(16)=71.5$
Adj. R-squared	0.061	0.140	0.171	0.164	*Prob*$>\chi^2 = 0.00$

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

VI. Case-Study Application of Loan Default Model

The analysis in the empirical specification effectively creates the foundation for a CDFI credit-scoring model. In the OLS regression, the coefficients indicate how much each variable influences the default rate. Suppose a simple model is the following:

$$P_{default} = (-0.038)*FICO + (-0.12)*LengthBus + 50.1$$

For loan Z, if the FICO score is 650 and the length in business is 5 years, then the $P_{default,z}$ is 24.8. We assign an in-house credit score of 248. In this example of an in-house model, lower scores are better because they reflect lower probabilities of default. For the *Strong/Not Strong* models, higher scores are better. For the *Weak/Not Weak* models, lower scores are better. Any of the regression tables could serve as a credit-scoring model, and all of the OLS models are the simplest to use because the loan officer would just multiply the coefficients by the independent variable values for the loan in question.

Overstreet and Rubin (1996) recommend that any credit-scoring model should be built on a set of past applications of at least 1,500 loans. Claire and Kossmann (2003) recommend 15,000 loans, and BankAmerica developed a model based on 15,000 good and 15,000 bad loans (Oppenheim 1996). X's dataset only includes 530 loans – a number far below the three recommendations. Customized score cards cost between \$35,000 and \$50,000, mainly due to the number of person-hours needed to sift through loan files (Overstreet et al., 1996). As noted earlier, it can take 20 to 45 minutes to identify and tally all of the required information for a loan file; assuming 1,500 loan observations, this could require 1000 person hours.

In addition, Regulation B of the Equal Credit Opportunity Act amendments of 1976 regulates what variables can be included in a credit score. Some of the barred variables include race, sex, color, religion, and information about marital status, childbearing preferences, and age

(Overstreet et al., 1996). Furthermore, if a variable (such as zip code) is highly correlated with another variable (such as race) and it is also a statistically significant predictor of repayment, it cannot be used because the chain of causality links it to a variable barred in Regulation B (Overstreet et al., 1996).

The results from the empirical section in Section V are stronger when tested. An optimal credit-scoring model uses 2/3 of the data to produce the model, and then tests the model on the "out-of-sample" data (the remaining 1/3). Given that the dataset already contains fewer than the optimal amount of loans, the predictive power would be greatly diminished if a model was created using just 2/3 of the 530 observations. Another way to test the accuracy of the model is use the odds-ratios. Using the logistic odds ratio probabilities and a threshold of >0.5 probability equals 1 and <0.5 probability equals 0, the accuracy of the *Strong/Not Strong All Loans* model is:

Table 13. *All Loans Strong/Not Strong Model correctly predicts 85% of the not strong loans*

		Predicted Values from Model		
		Predicted Not Strong	**Predicted Strong**	
Actual Data from Oct '09	**Not Strong**	235 85.14%	41 14.86	276 100%
	Strong	113 67.66%	54 32.34%	167 100%
	Total	348 78.56%	95 21.44%	443 100%

This means that with a 0.5 probability threshold, the *Strong/Not Strong All Loans* model correctly predicts a not strong designation 85% of the time and a strong designation 32% of the time. Considering that the R^2 value of the model is only 11%, this is a promising result.

It is difficult to compare these results to other studies, because few, if any, CDFIs have credit-scoring models, and there is a dearth of academic work on this subject. The internal Kinat Report at X created a model for SBA-only loans with a predictive power of 76% correct for "not weak" SBA loans. This model, as shown below, improves the predictive power by correctly predicting 95% of “not weak” loans for SBA and non-SBA loans combined. The *Weak/Not Weak All Loans* model predictive power is below:

Table 14. *All Loans Weak/Not Weak Model correctly predicts not weak 95% of the time*

Predicted Values from Model

Actual Data from Oct ’09		**Predicted Not Weak**	**Predicted Weak**	
	Not Weak	309 95.37%	15 4.63%	324 100%
	Weak	68 57.14%	71 42.86%	119 100%
	Total	377 85.10%	66 14.90%	443 100%

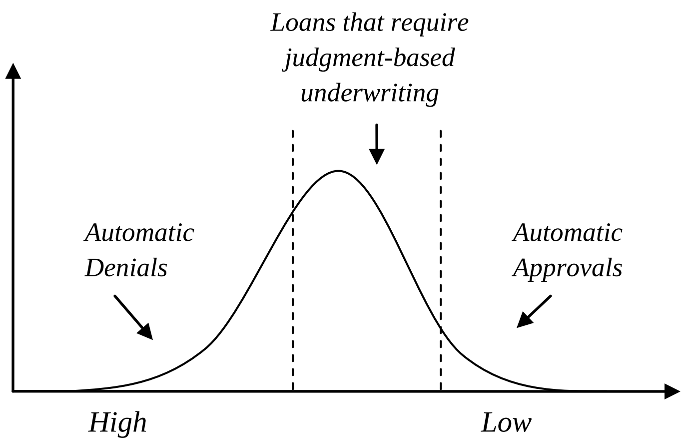
All of the models are better at predicting the “weak and medium” or the “strong and medium” combinations. Table 15 shows the correct predictions for each model:

Table 15. *Each loan’s predictive power using a 0.5 probability threshold*

	Correctly Predicted Strong	**Correctly Predicted Not Strong**
All Loans Strong Model	32%	85%
Start-Up Loans Strong Model	39%	85%
Microloans Strong Model	20%	90%
	Correctly Predicted Weak	**Correctly Predicted Not Weak**
All Loans Weak Model	43%	95%
Start-Up Loans Weak Model	40%	94%
Microloans Weak Model	43%	93%

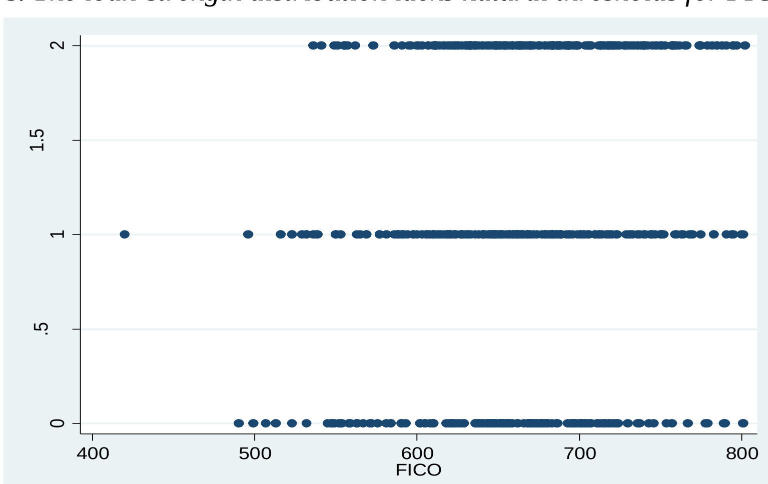
However, in the working world, a CDFI would be unlikely to use a 0.5 probability threshold and apply this credit-scoring model to all of the loans in their portfolio. It is more likely that a CDFI would want to use the model to identify which loans to automatically deny, automatically accept, and which would require additional attention.

Figure 7. *In a given CDFI portfolio, the credit-scoring can be used to predict the best and worst loans leaving the middle for additional underwriting*



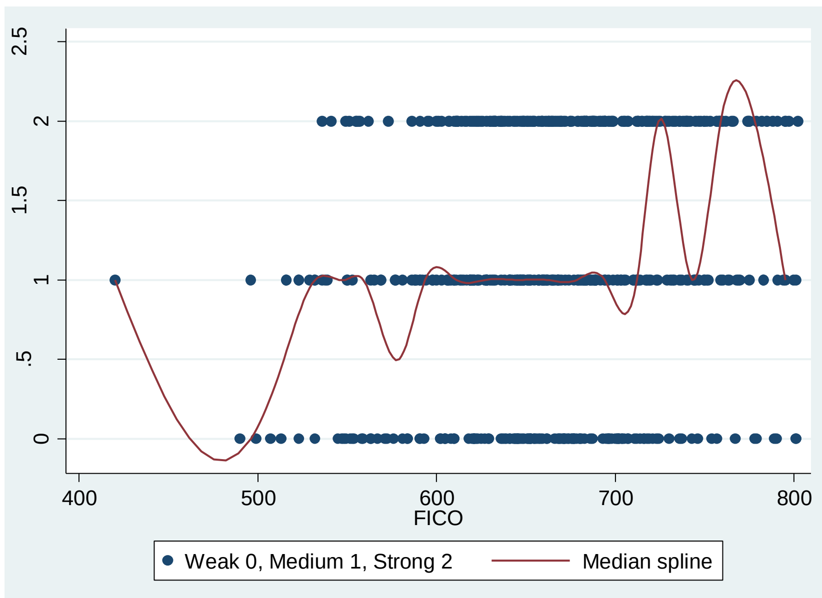
The decision of where to place the credit-scoring cut-off deserves some attention. If the cut-off score is too high, it would exclude many good loans, which is otherwise known as a "Type I" selection error. A high cut-off would significantly reduce the amount of profit a bank can expect to make on their loans. However, if the cut-off is too low, it would include many bad loans, referred to as a "Type II" selection error. Low cut-offs erode profits. In some samples, the cut-offs are obvious, especially when using a graph. Unfortunately, in this dataset, the cut-offs are not readily apparent. A strong loan is coded as (2), medium as (1), and weak as (0).

Figure 8. *The loan-strength distribution lacks natural thresholds for FICO score*



Splines, a mathematical method to determine the cut-offs in a dataset, are piecewise polynomial (parametric) curves. They can often fit clumped data better than higher degree polynomials. However, as shown by the oscillation, the spline function also does not indicate any natural thresholds between the loan-strength levels – strong, medium, and weak. Thus, the CDFI would have to internally set the cut-offs, which depend on its risk appetite for its portfolio.

Figure 9. *Even a spline function cannot separate the lack of differentiation between FICO and loan strength*



VII. **Conclusion**

Even though credit-scoring methods for consumers and credit cards have been well-developed over the past few decades, credit-scoring technologies are relatively new for small business loans. In 2007, Andrea Berger and Marisa Barrera noted that "to date, microlenders in the United States have not made use of statistical scoring."[14] In the past three years, some microlenders, such as ACCION USA, have started to develop and test statistical models. Even in CDFIs like X, whose portfolios extend beyond micro-borrowers, statistical scoring is starting to

[14] Berger and Barrera, pg. 4.

become more accepted. Additional papers in this field will be valuable, because many credit scoring methodologies, especially for consumers, are proprietary and confidential. As CDFIs are able to find ways to make these credit-scoring technologies less expensive, they would likely gain popularity if they do not cause the firm to “mission-drift” away. When more CDFIs publish their credit-scoring techniques, the results from this paper will become more relevant for comparison. Credit-scoring models are powerful tools because they can increase efficiency, streamline and cut costs in the underwriting process, and minimize human bias during origination.

It has become even more important during our recent recession to find better methods to manage the risk in a given CDFI portfolio. For instance, one of the nation’s largest CDFIs, ShoreBank in Chicago, has curtailed small business and real-estate lending in the past few months as it continues to search for additional investors to keep it out of bankruptcy. The factors that influence small business loan (SBL) defaults vary widely given different populations. Consequently, any credit-scoring system has to be designed individually for each institution.

In X’s data, FICO score is by far the most widely predictive measure. FICO scores are less influential in predicting micro-borrower default, likely because their credit scores are underrepresented, if represented at all, in national credit bureaus. Firms that spend many years in the business and are run by experienced managers often fare better than those who lack these skills. However, the number of years in business is, intuitively, not predictive for start-up loan defaults.

Loans with large government guarantees are much more likely to be weak. However, this variable was not significant for the micro-borrowers, suggesting that government guarantees are at times applied to the “right” kind of borrower: a strong borrower, who has had difficulty finding funds elsewhere because he or she is deemed “risky” by conventional measures. Government guarantees are supposed to help extend more credit into underserviced markets, which often correlates with riskier borrowers.

Borrowers who experience large changes in the local unemployment rate are more likely to default. Start-ups are especially sensitive to peak changes in unemployment, compared to all-loans or microloans. In general, variable interest rates are associated with weaker loans, especially for micro-borrowers, who have the most difficult time paying off variable rate loans. Loans with large deviations from prime are more likely to be weak, suggesting that the bank either uses some risk-based pricing or that more expensive loans are harder to pay off.[15]

In Section VI, the working-world application of the credit-scoring model outlined the percent of correct predictions for each model. Although there is a lack of other academic work to compare these results, this sets a baseline for the model’s accuracy. The cut-off points will have to be internally set by the CDFI, depending on its risk appetite. Considering the relative weaknesses of these models, credit-scoring should be used as a supplement, and it should not replace judgment-based underwriting entirely.

An overarching question in this field is whether credit-scoring models have inherent biases and disadvantage the target mission clientele. In other words, the CDFI questions whether following a more market-driven, profit-oriented model, typical of financial institutions, would lead it to “mission-drift” away from the social goal of alleviating credit barriers in distressed communities. Depending on the sub-population, it appears that sometimes females are associated with stronger loans and never weak loans. The minority dummy is never significant in any

[15] Currently the interest rate calculates are estimates. Future regressions will need to use better interest rate data.

model, corroborating the theory that this credit model would not cause the CDFI to “mission drift” away.

Future studies would benefit from drawing on larger datasets. The dataset should also contain better data on interest rates, and particularly how they affect the borrower’s payments each month. Additionally, loan repayments are not binary: “repaid” or “did not repay.” A loan that defaults the week after loan origination is different from one that defaults in the second year, and even if the CDFI recoups a percentage of the loan, it is better than nothing. Future research in this area should run a time-sensitive model that has the information on exact dates of initial arrears. Finally, as the CDFI collects more data from its hard-copy loan files, these models should be recalibrated.

Appendix A

Multinomial Logistic Regressions with Relative Risk Ratios

The results from a multinomial logistic regression are interpreted differently from an OLS regression. The multinomial results for *all loans* are found in *Regression 1.3 (pg. 59),* for *start-up loans* in *Regression 2.3 (pg. 61),* and for *microloans* in *Regression 3.3 (pg. 63).* In these multinomial regressions, the base variable is “weak.” Like the logit regression, multinomial logistic regressions also produce coefficients that cannot be directly interpreted. One way to make the regression easier to interpret is to use relative risk ratios. All of the subsequent tables report the relative risk ratios, which are like odds ratios.

In *Regression 1.3* for *all loans*, each year increase in management experience increases the odds of a weak loan to a medium loan by 4%. A female has 99% higher odds of having a medium loan than a weak loan. However, a female only has a 72% higher odds of having a strong loan than a man. Each 10 point increase in FICO contributes to a 8% higher odds of a medium loan than weak loan, and a 12% higher odds of having a strong loan than weak loan. Compared to a weak loan, each additional year in business increases the odds of a medium loan by 15% and a strong loan by 16% compared to a weak loan.

Government-backed loans are more likely to be weak or medium. Large deviations from the prime rate are more commonly found in weak loans than in strong loans: strong loans have 79% *lower odds* of having large deviations in the interest rate. Large changes in the unemployment rate are the most common in weak loans. Loans with large deviations in interest rates compared to the prime rate and given during healthy economic periods are less likely to be weak. In addition, loans with variable interest rates given during strong economic periods often fared better.

Regression 1.3 All Loans

Multinomial Logistic Relative Risk Ratios

VARIABLES	(1) *Base* Weak	(2) Medium	(3) Strong
Management Exp. *(yrs)*	1.000	1.042*	1.037
	(0.000)	(0.023)	(0.023)
Female *(dummy)*	1.000	1.991**	1.715*
	(0.000)	(0.591)	(0.509)
FICO	1.000	1.079***	1.116***
	(0.000)	(0.028)	(0.029)
Length Business *(yrs.)*	1.000	1.153**	1.155**
	(0.000)	(0.065)	(0.066)
Minority *(dummy)*	1.000	0.781	0.678
	(0.000)	(0.228)	(0.200)
Debt-to-income	1.000	1.157	1.059
	(0.000)	(0.162)	(0.213)
Age of loan *(months)*	1.000	0.986	0.979
	(0.000)	(0.015)	(0.015)
Gov't Guar. %	1.000	0.724***	0.759***
	(0.000)	(0.054)	(0.056)
Int Deviation from Prime	1.000	0.378	0.213**
	(0.000)	(0.239)	(0.139)
Ln(Loan Amount)	1.000	1.016	1.212
	(0.000)	(0.229)	(0.280)
Matured *(dummy)*	1.000	0.453	0.216**
	(0.000)	(0.253)	(0.131)
Variable Rate *(dummy)*	1.000	0.167	0.057
	(0.000)	(0.426)	(0.152)
S&P 500 at origination	1.000	0.950*	0.919***
	(0.000)	(0.029)	(0.030)
Peak Δ Local UR	1.000	0.762**	0.677***
	(0.000)	(0.092)	(0.089)
Interest Dev*S&P 500	1.000	1.007	1.014**
	(0.000)	(0.006)	(0.006)
Variable Rate*S&P 500	1.000	1.044*	1.053**
	(0.000)	(0.023)	(0.025)
Observations	443	443	443

LR $\chi^2(32) = 153.07$
Prob > χ^2 = 0.000

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

Regression 2.3 (pg. 61) contains the relative risk ratios for the multinomial logistic for the *start-up* loan subset of data. Start-up loans are defined as being in business for one year or less. Many of the outputs were similar to the all-loans multinomial analysis. The following highlights the differences.

The length of business is not significant in this model, which was also found in the binary models. This makes sense considering that the business is a start-up. Peak changes in the unemployment rate are more influential for the all-loans *medium* to weak, and not significant for the start-up *medium* to weak. However, for each 1% increase in the peak unemployment rate, the start-up loans have 64% lower odds of being *strong* compared to weak.

Regression 2.3 Start-Up Loans *Multinomial Logistic Relative Risk Ratios*

VARIABLES	(1) *Base* Weak	(2) Medium	(3) Strong
Management Exp. *(yrs)*	1.000	1.033	1.025
	(0.000)	(0.026)	(0.026)
Female *(dummy)*	1.000	1.968**	1.739
	(0.000)	(0.672)	(0.603)
FICO	1.000	1.071**	1.124***
	(0.000)	(0.031)	(0.034)
Length Business *(yrs.)*	1.000	1.004	0.832
	(0.000)	(0.394)	(0.348)
Minority *(dummy)*	1.000	0.881	0.670
	(0.000)	(0.296)	(0.235)
Debt-to-income	1.000	1.141	1.042
	(0.000)	(0.169)	(0.240)
Age of loan *(months)*	1.000	0.995	0.993
	(0.000)	(0.017)	(0.018)
Gov't Guar. %	1.000	0.764***	0.780***
	(0.000)	(0.067)	(0.070)
Int Deviation from Prime	1.000	0.468	0.233**
	(0.000)	(0.314)	(0.171)
Ln(Loan Amount)	1.000	0.806	0.991
	(0.000)	(0.218)	(0.277)
Matured *(dummy)*	1.000	0.450	0.175**
	(0.000)	(0.285)	(0.129)
Variable Rate *(dummy)*	1.000	0.725	0.018
	(0.000)	(2.057)	(0.056)
S&P 500 at origination	1.000	0.958	0.911**
	(0.000)	(0.031)	(0.033)
Peak Δ Local UR	1.000	0.805	0.637***
	(0.000)	(0.108)	(0.102)
Interest Dev*S&P 500	1.000	1.005	1.012*
	(0.000)	(0.006)	(0.007)
Variable Rate*S&P 500	1.000	1.028	1.066**
	(0.000)	(0.025)	(0.030)
Observations	309	309	309

LR $\chi^2(32) = 101.49$
Prob > $\chi^2 = 0.000$

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

Regression 3.3 (pg. 63) contains the relative risk ratios for the multinomial logistic on the *microloan* subset of data. Microloans are defined as $35,000 or less. Many of the outputs were similar to the all-loans and start-up multinomial analysis. The following highlights the differences.

Female micro-borrowers are three times more likely than men to hold a medium loan compared to weak, and twice as likely to hold a strong loan compared to a weak loan. This is a much higher rate than the all-loans and start-up analysis which indicates that women are twice as likely to hold a medium loan and 74% higher odds of holding a strong loan.

This regression also marks the first time that age of loan becomes significant. Microloans that are held for more months are more likely to be weak. This suggests that the more profitable microloans are those that are paid-off quickly. Especially considering that microloans have smaller loan amounts than other loans, this result makes sense. Microloan interest rates that have large deviations from the prime rate are much more likely to default than all-loans or start-up loans.

Additionally, variable rate microloans are almost unanimously predictive of being weak compared to strong or medium, which is not the finding in all-loans or start-up loans. This suggests that micro-borrowers have more difficulty paying variable rate loans.

Regression 3.3 Microloans *Multinomial Logistic Relative Risk Ratios*

VARIABLES	(1) *Base* Weak	(2) Medium	(3) Strong
Management Exp. *(yrs)*	1.000	1.043	1.028
	(0.000)	(0.032)	(0.033)
Female *(dummy)*	1.000	2.943***	2.179*
	(0.000)	(1.170)	(0.882)
FICO	1.000	1.112***	1.145***
	(0.000)	(0.038)	(0.040)
Length Business *(yrs.)*	1.000	1.203**	1.148*
	(0.000)	(0.088)	(0.087)
Minority *(dummy)*	1.000	0.953	0.570
	(0.000)	(0.358)	(0.221)
Debt-to-income	1.000	1.213	0.474
	(0.000)	(0.255)	(0.315)
Age of loan *(months)*	1.000	0.961**	0.958**
	(0.000)	(0.019)	(0.019)
Gov't Guar. %	1.000	0.553	1.261
	(0.000)	(0.295)	(0.527)
Int Deviation from Prime	1.000	0.008***	0.005***
	(0.000)	(0.014)	(0.009)
Ln(Loan Amount)	1.000	0.914	1.497
	(0.000)	(0.279)	(0.489)
Matured *(dummy)*	1.000	0.569	0.134*
	(0.000)	(0.526)	(0.145)
Variable Rate *(dummy)*	1.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
S&P 500 at origination	1.000	0.794***	0.763***
	(0.000)	(0.069)	(0.067)
Peak Δ Local UR	1.000	0.866	0.729*
	(0.000)	(0.136)	(0.136)
Interest Dev*S&P 500	1.000	1.044***	1.050***
	(0.000)	(0.017)	(0.017)
Variable Rate*S&P 500	1.000	1.315***	1.298***
	(0.000)	(0.118)	(0.112)
Observations	256	256	256

LR $\chi^2(32) = 96.30$
Prob > $\chi^2 = 0.000$

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

Appendix B

Analysis of the Outliers

Because individually-identifying information about borrowers is confidential and illegal to disclose, everything in this paper is displayed in aggregate. Loan default data can have multiple influencers, and as seen in this dataset, many of the variables are highly correlated. To see whether there are some commonalities between the outliers, I looked at the twenty best performing loans with bad FICO scores and the twenty worst performing loans with good FICO scores. Historically FICO scores should be the most predictive of loan repayment.

Best Performing/Bad Credit

- Smaller loan amounts
- Lower interest rate
- Older loan
- Almost all non-SBA
- More technical experience
- Less education
- Lower net worth
- Higher debt-to-income
- Lower post-loan debt-to-income
- Older businesses
- Female borrower
- More likely prior business owner

Worst Performing/Good Credit

- Larger loan amounts
- Higher interest rate
- Newer loan
- More likely SBA, much higher SBA guarantee than average
- More technical experience
- More education
- Lower net worth
- Lower debt-to-income
- Higher post-loan debt-to-income
- Start-up
- Male borrower
- Less likely prior business owner

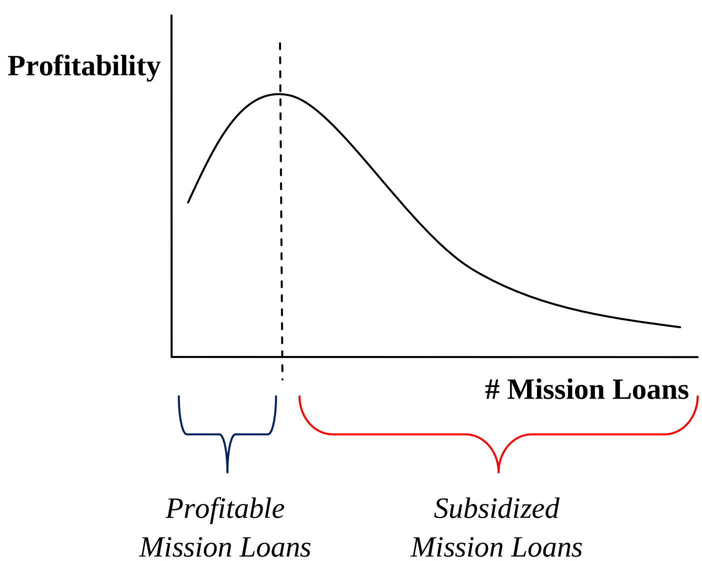
I use these outlier patterns to strategically select some of the variables in the economic specification.

Appendix C

The Profit and Social Mission Maximizing Functions of a CDFI

Profit information in most CDFIs, including X, is confidential. This dataset does not have access to X's costs or another method to analyze profitability. CDFIs are special case because the profitability for a CDFI does not only depend on the revenues; having more "mission borrowers" can also lower the firm's costs, which I describe in further detail below.

The costs to the bank are not known to the borrower and are unrelated to the borrower's default rate. However, subsidies and grants affect the level of costs for the firm. The CDFI seeks to *maximize the repayment rate* (minimize default) *subject to a high percentage of mission clientele in their portfolio*, which affects the firm's access to grants and subsidies.



One way a bank makes a profit is from charging a higher interest rate on their loans than the interest rate it pays on its rented capital. In the simplest banking model, a bank collects deposits and pays an interest rate to those depositors, and then it uses this money to give out loans with a higher interest rate. The bank profits on the spread between those rates.

However, in microfinance and community development banking, many banks have two other sources of capital inflow: grants and subsidies.[16] In the simple model, banks profit when their revenues *R* are larger than their costs *C*. Bank revenues (*R*) equal the revenues from small business loans (R_{SBL}) plus grant money (*G*):

$$R_{bank} = R_{SBL} + G \tag{1}$$

Bank costs (*C*) are equal to their selling, general, and administrative costs (*SGA*) plus the cost of rented capital (C_{RC}):

$$C_{bank} = SGA + C_{RC} \tag{2}$$

Because subsidized rented capital has a lower interest rate than the market interest rate, the costs for a subsidized bank are lower than one that operates on the market:

$$C_{subsidized} < C_{market} \tag{3}$$

Assuming that a bank's costs are fixed in the short term, and it cannot choose if it operates on subsidies or in the traditional market, a bank maximizes it profit (P) by maximizing its revenue:[17]

$$\max \ (P_{bank}) = \max \ (R_{bank}) - \bar{C} \tag{4}$$

Assuming that the grants a bank receives are fixed in the short term, the revenue maximization equation becomes the following:

$$\max \ (R_{bank}) = \max \ (R_{SBL}) + \bar{G} \tag{5}$$

The revenues from an individual small business loan (R_{SBLi}) depend on the price (the interest rate) of the individual loan (i_{SBLi}), size of the individual loan (s_i), and the probability that the individual loan will default (p_i).

$$R_{SBLi} = (1 + i_{SBLi})s_i * (1 - p_i) \tag{6}$$

[16] As defined earlier: *grants* are a source of revenue that the bank does not have to repay. *Subsidies* are defined as loans with subsidized interest rates – interest rates below market rates. Although these subsidized loans will have to be repaid, they are cheaper than the ones a bank would find on the market.

[17] If the costs are growing at an increasing rate, maximizing revenue does not always maximize profits. However, this problem assumes that costs are fixed in the short-run, which then follows that revenue maximization is profit maximization.

The total bank revenues from small business loans comes from the summation of all the individual revenues from the bank's small business loans:

$$R_{SBL} = \sum R_{SBLi} = \sum[(1 + i_{SBLi})s_i * (1 - p_i)] \tag{7}$$

I assume that the bank has a target size of the individual loan, which does not vary greatly and is based on the available underwriting funds. I also assume that the bank operates in a competitive environment, which means that the bank is a price-taker for the borrower's set interest rate (risk profile).[18] If the bank sets an interest rate that is much higher than the borrower would receive on the market, the borrower would look for a loan elsewhere. Therefore, the revenue maximization is the following:

$$\max \quad (R_{SBL}) = (1 + i_{SBLi})s_i * [\max(1 - p_i)] \tag{8}$$

In other words, a bank maximizes revenues when it minimizes the rate of default in the short-run. The grants and subsidies are conditional on many factors, including that the CDFI continues to invest in low-wealth, minority and/or female entrepreneurs. The CDFI can lend to any borrower, but if it increases its social mission, it also increases its profits through increasing available grants and subsidies. Thus, CDFIs are in a situation that is slightly different from the traditional profit-maximization question for a firm – CDFIs must be able to balance social mission maximization and default risk minimization to achieve profit maximization. CDFIs are also different from traditional banks because they may be willing to accept a lower or negative profit if the social gains are high enough and the costs to the CDFI are sufficiently subsidized with a grant or below market interest rates.

[18] *Caveat*: Because CDFIs are subsidized, they are not necessarily interest rate price-takers. They can choose if they want to pass along some form of subsidized rate to certain borrowers and still make a profit if this subsidized rate is greater than the rate the bank is paying on the rented capital. This leads to the following question: can CDFIs optimize which loans they give to which people? If the interest rates differ on the loans (this is true at X from the Kinat report) – is it better to give one group a higher interest rate than another? Should interest rates just be reflective of risk or do they also affect repayment? I address this question in Theoretical Section III.

Appendix D

F-Tests

All Loans, Strong/Not Strong Model

For all, we have four groups of variables: borrower, loan and lender, macro variables, and interaction terms.

- **Borrower**: Management Experience *(yrs)*, Female *(dummy)*. FICO, Length Business *(yrs.)*, Minority *(dummy)*, Debt-to-income
- **Loan and lender**: Age *(months)*, Gov't guar. %, Interest Deviation from Prime, Ln(Loan Amount), Matured *(dummy)*, Variable Rate *(dummy)*
- **Macro**: S&P 500 at Origination, Peak Δ Local Unemployment Rate
- **Interaction Terms** Interest Dev*S&P 500, VarInt*S&P 500

F-Test 1: Unrestricted (includes borrower, loan and lender, macro)

Restricted (includes borrower, loan and lender)

```
. test sp_orig_10 ur_devorig intdevxsp500 varintxsp500

 ( 1)  sp_orig_10 = 0
 ( 2)  ur_devorig = 0
 ( 3)  intdevxsp500 = 0
 ( 4)  varintxsp500 = 0

       F(  4,   426) =    2.62
            Prob > F =    0.0347
```

We reject the null at the 1% level. Therefore, the macrovariables are significant to whether or not a loan is strong.

F-Test 2: Unrestricted (includes borrower, loan and lender, macro)

Restricted (includes borrower, macro)

```
. test agem guar_10 intdevfrompr lnlamt matured varint

 ( 1)  agem = 0
 ( 2)  guar_10 = 0
 ( 3)  intdevfrompr = 0
 ( 4)  lnlamt = 0
 ( 5)  matured = 0
 ( 6)  varint = 0

       F(  6,   426) =    1.37
            Prob > F =    0.2259
```

We cannot reject the null. Therefore, the loan and lender variables without interaction terms may not be significant to whether or not a loan is strong.

```
. test agem guar_10 intdevfrompr lnlamt matured varint intdevxsp500 varintxsp500

 ( 1)  agem = 0
 ( 2)  guar_10 = 0
 ( 3)  intdevfrompr = 0
 ( 4)  lnlamt = 0
 ( 5)  matured = 0
 ( 6)  varint = 0
 ( 7)  intdevxsp500 = 0
 ( 8)  varintxsp500 = 0

       F(  8,   426) =    3.74
            Prob > F =    0.0003
```

However, with interaction terms *included*, we can reject the null at the 1% level, which means that loan and lender variables with interaction terms are significant to whether or not a loan is strong.

Additional F-stats are available from the author by request (arc14@duke.edu).

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