CENTER FOR
INDIAN COUNTRY
DEVELOPMENT
FEDERAL RESERVE BANK OF MINNEAPOLIS

WORKING PAPER SERIES | 2022-02

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NOVEMBER 2022

Valentina Dimitrova-Grajzl
Virginia Military Institute

Peter Grajzl
Washington and Lee University

Joseph Guse
Washington and Lee University

Michou Kokodoko
Federal Reserve Bank of Minneapolis

Laurel Wheeler
Federal Reserve Bank of Minneapolis

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Valentina Dimitrova-Grajzl[a] Peter Grajzl[b] Joseph Guse[c]

Michou Kokodoko[d] Laurel Wheeler[e]

November 2022

Abstract

Native community development financial institutions (Native CDFIs) have become an increasingly important source of credit and financial services in Indian Country. This paper provides the first systematic quantitative analysis of lending in the Native CDFI industry. Using loan-level data from 11 Native CDFI loan funds, we first document the characteristics of Native CDFI loans and clients. We then investigate the determinants of loan delinquency. Native CDFIs on average give out small loans but support borrowers in varied circumstances with diverse loan products. Important predictors of delinquency include both conventional industry measures of client risk and alternative community-informed and character-based measures. Indeed, evidence on performance of business loans suggests that a character-based measure of client risk dominates the credit score as a predictor of delinquency. These findings lend support to using holistic approaches for assessing client creditworthiness that have already been adopted by some Native CDFIs. More generally, our analysis contributes new insights into the operations of an industry that plays an instrumental role in removing barriers to socioeconomic development in Indian Country.

Keywords: Native CDFIs, Indian Country, lending, delinquency, character-based lending

JEL Classifications: G21, O16, J15, P43

* We are grateful to Krystal Langholz and Andrea Mader and, more broadly, to Oweesta and Sweetgrass Consulting, for working closely with us on the data collection and for many helpful discussions. We also thank Matt Gregg and Ryan Nunn for their insightful suggestions. The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

a Department of Economics and Business, Virginia Military Institute. Email: dimitrova-grajzlvp@vmi.edu

b Department of Economics, Washington and Lee University and CESifo, Munich, Germany. Email: grajzlp@wlu.edu

c Department of Economics, Washington and Lee University. Email: gusej@wlu.edu

d Community Development and Engagement, Federal Reserve Bank of Minneapolis. Email: michou.kokodoko@mpls.frb.org

e (Corresponding author) Center for Indian Country Development, Federal Reserve Bank of Minneapolis. Email: laurel.wheeler@mpls.frb.org

1. Introduction

Access to credit is a necessary condition for pursuing economic opportunities and enhancing financial security. Credit enables businesses to grow, individuals and households to build wealth and maintain steady patterns of consumption, and governments to fund investments in public goods. In Indian Country (areas with American Indian reservations), several barriers exist to accessing credit. Those barriers include the inability to use trust land as collateral, the jurisdictional maze that characterizes most tribal lands, and the relatively high rates of poverty resulting from centuries of forced relocation, assimilation policies, and discrimination. In addition, Native communities throughout the United States have been historically underserved by mainstream financial institutions such as banks and credit unions (see, e.g., Listokin et al., 2017; Jorgensen, 2016). According to a 2019 survey, approximately 16% of American Indian or Alaska Native households have no bank or credit union accounts (FDIC, 2020), higher than that of any other race group in the United States.[1] The problem is particularly acute on lands designated as federal Indian reservations, which tend to be geographically far from mainstream banks and ATMs (Jorgensen and Akee, 2017).[2]

Native community development financial institutions (Native CDFIs) are specialized financial institutions that fill the credit supply gap left by mainstream financial institutions in Indian Country (Kokodoko, 2015). CDFIs may be for-profit or not-for-profit, and they include loan funds, credit unions, banks, thrifts, holding companies, and venture capital funds. The common thread across CDFIs is their commitment to serving low-income communities by providing affordable loan products and tailored financial services (Kokodoko, 2015). Approximately one in 20

[1] Approximately 14% of Black, 12% of Hispanic, 2% of Asian, and 3% of white households report that they are unbanked (FDIC, 2020).
[2] The average distance from the center of the reservation to the nearest bank is approximately 12 miles and the average distance to the nearest ATM is approximately 7 miles (Jorgensen and Akee, 2017).

certified CDFIs are classified as Native CDFIs that predominantly target and serve American Indian, Alaska Native, and Native Hawaiian consumers (CDFI Fund, 2021).[3] Most Native CDFIs operate on tribal lands and are managed by tribal citizens. Many Native CDFIs also serve Native people living off tribal lands (Jorgensen, 2016). Importantly, Native CDFIs are mission-driven organizations with a focus on capacity building and community development (First Nations Development Institute, 2007). More broadly, they provide a private-sector, market-based approach to financial self-determination, a key driver of economic prosperity within Native Nations (see e.g., Cornell and Kalt, 2007).

When it comes to lending, what are some salient features of the Native CDFI industry? What factors shape the performance of Native CDFI loans? How relevant are conventional measures of client risk such as credit scores versus alternative metrics of client risk developed by Native CDFIs? Even though the Native CDFIs have emerged as increasingly important sources of credit for Native communities, due to a dearth of data, these central questions have not been empirically investigated in the context of the Native CDFI industry at large. Much of the scant existing literature is based on case studies or descriptive analyses that take a narrow focus on one facet of Native CDFI operations. The literature that is more generalizable to the Native CDFI industry as a whole has focused on the history and typology of Native CDFIs. Kokodoko (2015, 2017) analyzes the growth of Native CDFIs. Jorgensen and Taylor (2015) examine the impact of one Native CDFI, the Four Directions Development Corporation, on financial and community development of the residents of Indian Island, Maine. Dewees and Sarkozy-Banoczy (2008) explore five

[3] As of July 2022, there were 1,372 Certified CDFIs operating in the United States (CDFI Fund, 2022). CDFI Certification is a designation given by the U.S. Department of Treasury's CDFI Fund. The CDFI Fund was established in 1994.

Native CDFIs and their role in fostering entrepreneurial activity in Native communities.

In this paper, we advance the scholarship on Native CDFIs by providing the first systematic quantitative, loan-level inquiry into the operations of the Native CDFI industry. Using several years of originally collected loan-level data from 11 Native CDFIs,[4] we first perform a descriptive analysis of loan and client characteristics. We then exploit the fine-grained nature of our data to investigate the determinants of loan delinquency for different loan categories (business loans, home loans, and other consumer loans). To this end, we estimate a series of loan-level regressions to identify the loan and borrower characteristics that are prominent predictors of delinquency. Understanding the determinants of delinquency is of key importance because the ability to predict and mitigate delinquency enables Native CDFIs to effectively leverage their scarce capital and enhance their ability to meet community demand for credit.

Our descriptive analysis shows that Native CDFIs support borrowers in diverse circumstances and provide a variety of products. Although the exact bundle of services and products varies across Native CDFIs, all Native CDFIs are driven by the shared mission of supporting the economic development of Native communities. They also fill a gap and provide credit to people who would not be able to access credit via mainstream financial institutions. The Native CDFIs in our sample serve a significant number of clients with limited or no credit histories. Thus, an important product in consumer lending is the credit-builder loan, which helps clients enhance their credit history.[5] Our data show that Native CDFI loans are smaller on average

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[4] The organizations in our sample are loan funds, the most common type of CDFI. They are all nonprofit organizations. To fund their operations, in addition to reinvesting own returns from lending, they mostly rely on external grants and contributions.

[5] In the financial industry, a credit-builder loan generally holds the amount borrowed in a bank account while the borrower makes payments, thereby building credit. In our context, however, credit-builder loans refer to small loans intended to help members of Native communities build their credit history.

than loans from a commercial bank. Most loans in our dataset would be considered micro-loans. Accordingly, our data suggest that Native CDFIs offer their borrowers an opportunity to access credit, improve their financial literacy, and build and strengthen their credit performance and history.

Our empirical inquiry also reveals information about the lending practices of Native CDFIs. To assess borrower creditworthiness and increase consistency in decision making, mainstream financial institutions rely predominantly or exclusively on credit scores calculated by one of the major credit bureaus (Equifax, Experian, and TransUnion). Our loan-level regression analysis suggests that the credit score, a proxy for the borrower's credit history, is, at least when considered on its own, a salient predictor of Native CDFI loan performance. In nearly all estimated specifications and across all loan categories, we find that the likelihood of loan delinquency exhibits a statistically significant negative association with the borrower's credit score. In this sense, our findings show that conventional measures of borrower creditworthiness are relevant predictors of loan performance in Native communities.

Credit scores, however, may be a weak signal of a borrower's creditworthiness in underserved markets, where individuals have had little opportunity to develop a credit history.[6] Notably, more than 20% of Americans have either a thin credit file, stemming from insufficient credit history to calculate a credit score, or no credit history at all (Bureau of Consumer Financial Protection, 2021). For American Indian reservations, average credit scores are 30 points lower than they are in adjacent or nearby regions (Dimitrova-Grajzl et al., 2015). In addition, on reservations, the percentage of thin files is higher than in the nearby regions (ibid.). For these reasons, most Native CDFIs do not rely solely on credit score to screen loan applicants. To

[6] Credit reporting may also be a weak signal for borrowers belonging to various minority groups that have historically been affected by economic discrimination, such as redlining practices.

determine the types of loan products or services a client may need, many Native CDFIs supplement credit scores with community-specific information not adequately captured by the factors that comprise a standard credit score. One of the defining features of Native CDFIs is their focus on relationships and cultural fit (First Nations Development Institute, 2007; Jorgensen, 2016). Native CDFIs leverage their immersion in Native communities to assess the financial preparedness of borrowers with weak or non-existent credit histories. The corresponding lending approach epitomizes the so-called character-based model of lending, a strategy whereby the lender incorporates subjective information about potential borrowers' character to provide credit to clients that would otherwise be labeled as "high risk" (Melnick, 2021). This practice has empirical backing: research suggests that loan outcomes are associated not only with credit scores but also with character assessments and the social and cultural appropriateness of the loan products (Lee, 2019; Pickering and Mushinski, 2001). In an international context, reliance on character-based lending resonates with the strategy adopted by a subset of Japanese and Dutch lenders that regularly incorporate alternative indicators of an individual's creditworthiness, such as length of employment and proof of paying bills on time (see e.g., Curley, 2018; Gallo, 2022).

We find compelling evidence that, in Indian Country, non-conventional measures of client risk may be as important predictors of loan performance as conventional measures, such as credit scores. According to our data, even after controlling for the credit score, loan delinquency is less likely when the Native CDFI perceives the borrower as "somewhat engaged" as opposed to non-engaged. We also find that, when it is recorded, character score—a measure of community reputation and qualifications to run a business—has a statistically significant negative association with the prospect of delinquency. Perhaps most notably, the inclusion of the character score variable among the covariates renders the credit score statistically insignificant as a predictor of business loan delinquency. Further exploration of the data shows that this finding is not an artifact of multicollinearity: credit score and character score clearly reflect different underlying variation in the data.

Our results therefore lend support to a model of lending that is not narrowly centered on conventional metrics, such as credit scores, but instead adopts a holistic approach to assessing borrower creditworthiness. Interestingly, the importance of inclusion of non-conventional risk factors in loan underwriting models has been well understood at an intuitive level by practitioners in the Native CDFI industry. After all, this is the very reason why Native CDFIs have already attempted to gather data on alternative measures of creditworthiness that extend beyond measures such as the credit score and income. Our empirical analysis demonstrates that the reliance on the corresponding information and knowledge can indeed be a productive practice for the Native CDFI industry, and thus the prosperity of the Native communities.

The paper proceeds as follows. Section 2 discusses our data. Section 3 offers a descriptive account of the characteristics of Native CDFI loans and clients based on our data. Section 4 describes and discusses an empirical analysis of the factors that predict delinquency in Native CDFI loans. Section 5 concludes.

2. Data

Our loan data come from participating Native CDFIs that submitted information to the Oweesta Corporation and Sweet Grass Consulting, LLC, following an invitation to contribute to a research project on lending and risk analysis in the Native CDFI industry.[7] Sweet Grass Consulting invited fourteen Native CDFIs;

[7] Oweesta Corporation (Oweesta, for short) is the "longest standing Native CDFI intermediary offering financial products and development services exclusively to Native CDFIs and Native communities. Specifically, Oweesta provides training, technical assistance, investments, research, and policy advocacy to help Native Communities develop an integrated range of asset-building products and services, including financial education and financial products" (https://www.oweesta.org/about_native_cdfi/). Sweet Grass Consulting, LLC provides "professional consulting services around impact, research, and strategy that promote and support asset-based initiatives in economically burdened communities" (https://www.sweetgrassconsulting.net/).

eleven of those participated. The participating Native CDFIs are representative of the industry in terms of loan products, portfolio size (total dollar amount and total number of loans), and loan disbursement (average loan amount and number of loans per year). The overall volume of lending of the eleven participating Native CDFIs amounts to approximately 15% of the lending of the Native CDFI industry as a whole.

Table 1 shows the list of participating Native CDFIs. Respondents provided individual loan-level portfolio data and the associated risk-rating metrics. The set of participating Native CDFIs includes two of the oldest Native CDFIs – Lakota Funds (established in 1986 on the Pine Ridge Reservation in South Dakota) and Sequoyah Fund (established in 1996 by the Eastern Band of Cherokee Indians in North Carolina). The other nine Native CDFIs serve different geographic regions in the lower 48 states and Alaska. Sweet Grass Consulting consolidated the data and shared it with the research team.

The dataset covers business loans, home loans, and other consumer loans. Importantly, our data include only a sample of loans that the participating Native CDFIs disbursed during the time period under consideration. This includes loans that were active, loans that had been paid in full, and loans that had been declared bad debt (i.e., unrecoverable and charged off) at the point of data collection. Also, there was oversampling of loans that had experienced delinquency. In Sections 3 and 4 we elaborate on and discuss the implications of this sampling decision for our analysis.

3. What Are the Characteristics of Native CDFI Loans and Clients?

In this section we draw on our data to provide an overview of the characteristics of Native CDFI loans and clients. We first offer insights based on the combined sample of loans that aggregates business, home, and other consumer loans. We then offer insights based on each individual loan category.

3.1. Combined Sample

The dataset contains cross-sectional, loan-level data for 484 business loans, 305 home loans, and 1,276 other consumer loans (e.g., auto loans, employee loans, credit-builder loans). Table 2 reports the number of loans for each loan type by loan category: business, home, and other consumer loans. In the business loan category, micro-loans (188 loans) represent the most common loan type. The majority of loans in the home-loan category are second mortgages (206 loans). Among other consumer loans, the two leading types of loans are auto loans and employee loans. The employee loans are loans to employees of a tribal nation associated with the Native CDFI. The third largest type of other consumer loans are credit-builder loans (147 loans).

Table 3 shows loan counts based on loan delinquency status across the three loan categories. Not all Native CDFIs use and report consistent delinquency measures. Thus, in our data, loans are considered delinquent if they were delinquent at any point during the loan process and by any amount; loans are considered not delinquent otherwise. In addition, because loan delinquency is relatively uncommon among loans issued by Native CDFIs, delinquent loans were intentionally oversampled to enable meaningful analysis of the predictors of delinquency. The oversampling of delinquent loans in addition to the use of the broad definition of delinquency further explains why our data overstate the actual incidence of loan delinquency faced by Native CDFIs.

Table 3 indicates that as many as 17% of the business loans in our dataset were ever delinquent. As expected, given the oversampling of delinquent cases, this is a much higher delinquency rate than the 3.9% mean 90+ day delinquency rate reported for the Native CDFI industry as a whole in 2020 (Oweesta 2021). In our data, 8% of home loans and 11.5% of other consumer loans were delinquent, compared to the respective 1.8% and 3.7% mean 90+ day delinquency rate for the Native CDFI industry as a whole (ibid.).

The probability of delinquency may be affected by several borrower attributes and loan characteristics. One of the most utilized predictors of delinquency is borrower credit score. Credit scores vary between 300 and 850, with scores above 740 considered very good/excellent. Individuals with scores below 670 are subprime borrowers and are likely to experience difficulty qualifying for loans at mainstream banks.[8] Credit scores are often missing in our data. Out of 2,067 loans in our dataset, only 1,220 (59%) have credit scores. The absence of credit scores might be driven by thin files (files with an insufficient credit history to allow for calculation of a credit score) or by data not being recorded. For most of the Native CDFIs in our data, with one exception, we unfortunately cannot ascertain why credit scores are missing. For the one exception, borrowers have thin files in 150 out of 576 other consumer loans. Table 4 breaks down credit scores by loan category and delinquency status. The data indicate that borrower credit scores are significantly lower for other consumer loans than for business loans or home loans. This pattern may be explained by the fact that some of these consumer loans are credit-builder loans specifically designed for consumers with the lowest credit scores or with thin files. Figure 1 shows the distribution of loans by borrower credit score for each loan category.

Most business loans that appear in our dataset would be considered micro-loans.[9] Overall, we have 1,487 loans (business, consumer, and home) with non-missing loan

[8] See, for example, https://www.equifax.com/personal/education/credit/score/what-is-a-good-credit-score/.

[9] The CDFI Fund Transaction Level Reports' (TLR) definition of a micro-loan is: "Financing to a for-profit or non-profit enterprise that has five or fewer employees (including the proprietor) with an amount no more than $50,000 for a purpose that is not connected to the development (including construction of new facilities and rehabilitation/enhancement of existing facilities), management, or leasing of real estate."

amount values. The mean loan amount is $33,672 and the median is $5,500. Business and home loans tend to be larger than other consumer loans, although there is a great deal of variation both across and within loan categories. Figure 2 shows the distribution of loan amounts by loan category. Our dataset covers loans that were issued over a span of 19 years. The loan closing dates range from 2003 through 2021, with most loans issued between 2015 and 2020. Figure 3 shows the frequency of loan closing dates.

3.2. Business Loans

The business loans dataset contains information from five Native CDFIs on 484 business loans with closing dates between 2003 and 2021. Most loans were issued between 2016 and 2021. The loan types are identified as regular business loan, commercial loan with real estate, micro-loan, vehicle loan, equipment/inventory loan, artist loan, participation loan, rehab loan, and line of credit. The loan amount ranges from $250 to $2,259,865, with mean and median loan amounts of $60,016 and $23,300, respectively. For comparison, in 2017 the mean loan amount extended by all domestic banks for all commercial and industrial loans was $107,000; the mean loan amount extended by small domestic banks was $165,000.[10]

In our sample, the businesses that took out loans ranged from brand-new businesses to businesses that had existed for 23 years (276 months). Most businesses in our sample operate in agriculture (84 loans), transportation (74 loans), construction (48 loans), food services (23 loans), and retail (20 loans).

The borrowers range in age from 21 to 83 years. Of the 435 loans where both the amount of the loan and the gender of the borrower are known, 138 (32%) are issued to women. We do not observe educational attainment for all borrowers, but among the 210 borrowers (44%) for whom we do have information on attained education,

[10] These statistics pertain to the loans backed by the Small Business Association, https://www.federalreserve.gov/releases/e2/current/#fn6.

92.4% have at least completed high school and 24% have a bachelor's degree or higher. Most borrowers (353 or 82%) are American Indian, Alaska Native or Native Hawaiian (AIANNH). Approximately 10% of borrowers of business loans are repeat clients.

We do not observe credit score for all business loan borrowers in our sample but, among those for whom we do, credit scores range from 468 to 810. We do not observe credit score for 142 borrowers in the business loan dataset. With the exception of loans from one Native CDFI, it is not clear whether borrowers with missing credit score have thin files, the Native CDFI did not take the credit score into consideration when issuing the loan, or the credit score was simply not reported to us. The historical lack of access to mainstream financial institutions on American Indian reservations raises the question of the appropriateness of relying solely on credit scores in underserved communities. One concern is possible bias in the credit score, leading to ratings of trustworthiness that do not necessarily reflect the borrower's likelihood of repaying a loan. We discuss this issue in more detail in Section 4.3.

3.3 Home Loans

Mortgage lending in Indian Country has been historically difficult due to the complexity of land tenure issues (Listokin et al., 2017). However, since the passage of the 1996 Native American Housing Assistance and Self-Determination Act (NAHASDA), at least some of the hurdles to mortgage lending have been removed. Consequently, a subset of Native CDFIs focus primarily on mortgage lending. Other Native CDFIs have yet to develop their mortgage lending programs.

Our home loans dataset contains information on 305 home loans with closing dates ranging from 2015-2021. These include 94 first-mortgage loans, 5 construction loans, and 206 second-mortgage loans. The loan amounts for home loans range from $5,547 to $255,000, with a mean of $63,495 and median of $47,114. Credit scores are missing for 8 of the 305 home loans. For the remaining 297 loans, the credit scores range between 511 and 814, with the mean credit score equal to 697. Approximately 48% of home loans are issued to AIANNH borrowers. 57% of the borrowers are women. The average age of borrowers for home loans is 37 years, with a minimum of 18 years and a maximum of 79 years. Of the 222 loans for which the education attainment level of the borrower is known, all borrowers have at least a high school diploma and approximately 29% (64 loans) have a bachelor's degree or higher level of postsecondary education. Household size of borrowers, measured with the number of household members, ranges from 1 to 10 with a mean of 2.7 and median of 2. Approximately 14% of borrowers are repeat clients.

3.4. Other Consumer Loans

We have information on 1,278 consumer loans (outside of the home loan category). The most common loan types in this category are automobile loans (38%), employee loans (37%), and credit-builder loans (12%). Debt consolidation, emergency, home improvement, and rental assistance loans each represent 1% or less of the sample. We do not observe the closing date for 45% of the loans in this subsample. The closing dates that we do observe indicate that the loans were issued between 2014 and 2020, with the vast majority issued between 2018 and 2020. The loan amounts range from $408 to $26,226, with a mean of $2,544 and a median of $2,085.

There is incomplete information about the demographic characteristics of the borrowers for this loan category. Only two Native CDFIs report the age, race, and gender of their borrowers. For those loans, the available data indicate that borrowers range in age from 18 to 96 years. Of the loans from these two Native CDFIs, 59%

were issued to women and 93% were issued to borrowers with tribal affiliation. Only one Native CDFI reports the educational attainment of borrowers. Among the 127 borrowers (10%) for whom we have the information on educational attainment, 17% have a bachelor's degree or higher and 88% have a high-school degree or higher. We are missing credit score information for 694 borrowers (54%). This high percentage of borrowers partially reflects the fact that a significant number of these loans are credit-builder loans. For borrowers with a (reported) credit score, the scores range from 445 to 757.

The average borrower in this loan category has a household size of 2.5 household members (based on 206 observations) and annual household income of approximately $40,000 (based on 728 observations). The median household income is $31,000. About 60% of borrowers of other consumer loans are repeat clients.

3.5. The Main Takeaways

The descriptive analysis in Sections 3.1-3.4 shows that Native CDFIs provide a variety of products across the three broad categories of business, home, and other consumer loans. Unsurprisingly, Native CDFI loans are on average smaller than the loans of mainstream commercial banks. Native CDFIs, however, support borrowers in varied circumstances. Our data show that they serve a significant number of clients with limited or no credit histories and extend credit to both nascent and mature businesses that operate in a wide spectrum of industries. Although the exact bundle of services and products varies across Native CDFIs, the lending practices of Native CDFIs align with their shared mission of supporting the economic development of Native communities. Native CDFIs thereby fill the gap in the supply of credit not provided by mainstream financial institutions.

4. What Predicts the Delinquency of Native CDFI Loans?

Loan delinquency affects the financial sustainability of Native CDFIs, hampering their ability to extend credit in the future. It is therefore important to understand which loan or borrower characteristics are empirically prominent drivers of delinquency. We tackle this question in the subsequent analysis. We first lay out our empirical approach. We then present evidence based on both the combined sample and sub-samples by specific loan category.

4.1. Empirical Approach

To investigate the determinants of delinquency, we estimate a series of linear probability models (LPMs) using ordinary least squares (OLS). The parameter estimates of the LPM are readily interpretable as the average marginal effects on the probability of delinquency. We base inference on heteroskedasticity-robust standard errors.

Our dependent variable is a dummy equal to one if a loan is delinquent at any point during the life of the loan and by any amount, and zero otherwise. In the baseline specification, our explanatory variables are credit score, log household income, a dummy for a female borrower, a dummy for an AIANNH borrower, borrower age (in years) at the closing date of the loan, and a set of dummy variables capturing the borrower's attained education level (below high school, high school or associate degree, some college, bachelor's degree or higher). Many variables in our data have missing values. Simultaneous inclusion of many covariates thus quickly reduces our usable sample size. In augmenting the baseline specification, we therefore add additional explanatory variables one at a time.[11]

In models exploiting the combined sample of business, home, and other consumer loans, we always include fixed effects for Native CDFI by broad loan

[11] Summary statistics for the different samples we draw on in the various empirical specifications are included in an appendix that is available upon request.

category. The inclusion of the corresponding set of fixed effects is intended to absorb the effect of any inherent differences across the Native CDFIs and loan categories, as well as the interaction of these two factors, on loan delinquency. In models drawing on data for a specific loan category, we instead control for Native CDFI fixed effects.[12] For any given set of the estimated models, controlling for the applicable sets of fixed effects renders more tenable the ceteris-paribus interpretation of the effects of other borrower- and loan-level factors that are the focus of our analysis. However, we nevertheless caution against interpreting any of the effects as causal. As emphasized in Section 3.1, our loans are oversampled based on the outcome of interest (delinquency), rendering our data susceptible to sample selection concerns. In addition, there are possibly relevant borrower or loan characteristics that we do not observe and that could confound the estimated effects.

4.2. Evidence from the Combined Sample

We first explore the determinants of delinquency for the combined sample of business, home, and other consumer loans.[13] Table 5 presents the corresponding regression results. Column (1) shows the results for the baseline specification. Column (2) shows the results for an extended specification discussed below.

Standard risk-assessment models, used by mainstream financial institutions to evaluate loan applications, emphasize credit score and borrower income. We explore the predictive power of credit score and income. We find that credit score in

[12] We do not include year fixed effects for several reasons. First, we do not have information about the timing of all delinquencies of loans. We could control for the closing date/year of the loan, but this is an imperfect way to control for the effect of macroeconomic business cycles on repayment, because loans with the same closing year may have very different term lengths. Second, the majority of the loans in our dataset were issued between 2015-2020, which is post-recession and pre-pandemic. NCDFI-by-loan-category fixed effects largely subsume the time variation outside of that period. Nevertheless, we perform a robustness check in which we control for closing year in our analysis (available upon request); our results remain qualitatively the same.

[13] For all specifications, we ran the regressions with and without outliers. We only report the results without the outliers. In this specification, we exclude observations with household income below $2,500 and above $175,000, with the cutoffs selected based on analysis of a histogram of the income amounts. Our results are qualitatively the same, whether we include or exclude outliers.

particular has a highly significant association with delinquency in both specifications for the combined dataset (columns (1) and (2)). This suggests that for those borrowers who have a credit score, the credit score is a good predictor of delinquency. The point estimate suggests that a 100-point increase in credit score is associated with a 7-percentage point decrease in the likelihood of delinquency.[14] Household income, however, is not statistically significantly associated with delinquency in either of the specifications in Table 5. These findings suggest that at least some of the standard risk measures used in the broader industry might be less relevant for the construction of risk assessment models relevant to the Native CDFIs. Income, in particular, does not seem to be a good signal of creditworthiness in relatively high-poverty areas, such as Indian Country. Our informal discussions with Oweesta, Sweet Grass Consulting, and the Native CDFIs reveal that Native CDFIs are aware of this and have calibrated their approach to reflect it.

Perhaps unsurprisingly, to predict loan repayment, Native CDFIs have thus developed alternative measures of risk based on client engagement, character score, and commitment to business. The use of these and other non-conventional measures of credit risk is a defining feature of character-based lending (CBL). CBL recognizes that conventional lending may widen inequality by disadvantaging prospective borrowers who have not had the opportunity to demonstrate financial preparedness (Melnick, 2021). It also directly incorporates the fact that lenders in small communities may reduce uncertainty by building or relying on relationships with clients.[15] The CBL model appears to be gaining traction in practice but remains

[14] A 100-point increase in credit score is close to a one standard deviation increase. Based on the sample used in Table 5, a one standard deviation increase or decrease would correspond to an 81-point increase or decrease. Therefore, our point estimate indicates that a one standard deviation increase in credit score is associated with a 5.67 percentage point decrease in the likelihood of delinquency.

[15] According to Lee (2019, p.2), "[t]he Central idea of CBL is to make lending decisions based on borrowers' character rather than on borrowers' financial conditions in hopes of helping those who are considered high risks for lenders to provide credit and business opportunities."

under-studied quantitatively. We explore the relationship between delinquency and several of the non-standard measures employed by Native CDFIs and available to us in the various regression specifications below.

The first among these alternative measures used by Native CDFIs across all three loan categories in our dataset is client engagement. The specification in column (2) of Table 5 augments the baseline specification in column (1) by adding dummy variables measuring the level of client engagement. Client engagement is a variable that the loan officers assign to a borrower based on the perceived responsiveness and engagement of that borrower. The original variable is ranked on the scale of 1 to 5, where 5 denotes a very engaged client and 1 a client that is not at all engaged. We use this variable to define three levels of client engagement and the corresponding dummies: well engaged (original variable equal to 5); somewhat engaged (original variable equal to 3 or 4); and not engaged (original variable equal to 1 or 2), the comparison category.

Our estimates suggest that clients who are somewhat engaged have a lower probability of delinquency than clients who are not engaged (Table 5, column (2)). However, the probability of delinquency is not monotonic in the level of client engagement. Well-engaged clients are less likely to have delinquent loans than unengaged clients, but they are more likely to have delinquent loans than the somewhat-engaged clients. Coefficients on well-engaged and somewhat-engaged dummies are statistically significantly different at the 1% level. There are several possible explanations for this result, including that well-engaged clients may be those with less borrowing experience. We are, however, unable to directly test this hypothesis.

Client engagement is the only alternative measure to capture CBL that is available across all loan categories. In Section 4.3 we explore alternative measures, such as character score and commitment to business that are only available for the business loan category.

Finally, we briefly discuss the remaining covariates included in the models featured in Table 5. The key demographic characteristics of borrowers—gender, age, and ethnicity—are not statistically significant predictors of loan delinquency. Surprisingly, the estimated coefficients on the dummies for attained level of education indicate that, relative to not completing high school, having completed high school or higher level of education is associated with greater prospects of delinquency. This is likely driven by the fact that, relative to borrowers who have completed high school, borrowers who have not completed high school are much more likely to receive credit-builder loans.[16] The credit-builder loans are purposefully designed to be less risky (e.g., shorter term, smaller loan amount, or loan paid before money can be accessed by the borrower) and thus less likely to result in delinquency.

4.3. Evidence from Business Loans

Table 6 reports the estimation results for the category of business loans only. Column (1) reports the coefficients from the baseline specification. Subsequent columns extend the specification from column (1). Column (2) adds the covariate measuring the number of months that the business has existed. Column (3) adds dummy variables for assessed levels of commitment to business, a variable we discuss below. Column (4) adds a measure of the value of invested equity. Finally, column (5) presents the results based on a model in which all covariates are included simultaneously.

[16] Among the borrowers with a less than high school education, 14 had credit-builder loans, 1 had a business loan, and 10 had micro-loans.

Congruent with the results reported in Table 5, the estimates in Table 6 show that, in the context of business loans, some of the standard measures of risk assessment, such as household income (columns (1)-(5)) and equity invested (column (4) and column (5)) are not systematically related to prospects of loan delinquency. However, credit score (columns (1)-(5)) and longevity of the business (columns (1) and (5)) are statistically significantly and negatively associated with loan delinquency. Our point estimates suggest that a 100-point increase in credit score is associated with a 12-14 percentage point decrease in the likelihood of delinquency depending on the specification. Increasing the age of the business by 4.5 years is associated with a 6-percentage point decrease in the likelihood of delinquency.[17] A score of commitment to business is used by several Native CDFIs in our dataset. We include a set of dummies respectively indicating “more commitment to business” and “less commitment to business,” with “no commitment to business” as the omitted (benchmark) category (columns (3) and (5)). We do not find a statistically significant relationship between these variables and delinquency, although the point estimates are consistently negative, as anticipated.

One of the Native CDFIs in our dataset, Four Bands Community Fund, developed a character score as an additional CBL measure to include in their risk assessment model of business loans. The concept behind the character score is rooted in the idea of relationship-based lending. The loan officers have extensive conversations with the clients and build a relationship with their clients. Based on these conversations, they fill in missing information and then assign borrowers a character score based on a variety of factors, including role in the community, support networks, relationship with the CDFI, reputation in the community, overall financial literary

[17] According to the sample used to estimate the specification in column 2, a 4.5-year increase in business history is approximately equivalent to a one standard deviation increase. The mean value for business history is 54.3 months and the standard deviation is 54.9 months.

and personal stability. Importantly, the Four Bands Community Fund assigns the character score at the time of underwriting the loan. We run a separate analysis on the data from the Four Bands Community Fund to assess the association between their internally developed character score and the prospects of loan delinquency. Table 7 presents the results.

We first estimate a model with the credit score but without the character score (Table 7, column (1)). Congruent with the estimates in Tables 5 and 6, we find that the credit score is statistically significantly (at the 1% level) and negatively associated with delinquency. However, this association becomes statistically insignificant when we add character score among the covariates. Specifically, a regression that includes both the credit score and the character score (Table 7, column (2)) shows that, first, the credit score is no longer statistically significantly related to the prospects of loan delinquency and, second, that a higher character score is associated with lower likelihood of loan delinquency. In this sense, in our data, the character score dominates the credit score as a predictor of business loan delinquency.

One potential concern about the above finding is that the credit score and the character score may be highly correlated and therefore reflect the same underlying variation. In that case, the absence of a statistically significant association between the prospects of loan delinquency and the credit score upon the inclusion of the character score variable in our estimated model might simply be an artifact of multicollinearity. We find that this is not the case. The raw correlation between the credit score and the character score is positive but relatively weak (correlation coefficient of 0.35). The variance inflation factor (VIF), a standard diagnostic measure for detecting multicollinearity concerns, equals 1.35 for the credit score and 1.27 for the character score. For the estimated model as a whole, the mean VIF is 2.07. These VIF values are much smaller than 10, the rule-of-thumb value indicative of multicollinearity concerns (Wooldridge, 2013: 98). Consistent with this finding, an analysis of the data in our regression sample shows that borrowers with very good and excellent credit scores consistently get high character scores, but there is a substantial number of borrowers with fair credit scores who also get high character scores. Thus, the character score and the credit score decidedly do not reflect the same underlying variation in the data. Rather, the character score as a predictor of delinquency captures factors that are not incorporated in the credit score measure. All in all, our results thus lend support to the interpretation that, in Native communities, reliance of character-based and relationship-based lending might improve loan outcomes relative to pure reliance on credit score-based lending.

The central result about the importance of character score as a predictor of loan performance survives the inclusion of additional covariates. In columns (3)-(5) of Table 7, we include as controls business history months (column (3)), dummy variables indicating the level of commitment to business (column (4)), and logged equity invested (column (5)). The Four Bands Community Fund also provided data on lending hours defined as the total number of hours that a loan officer spent putting together the pertinent loan package and working towards closing. Column (6) in Table 7 further includes lending hours. Interestingly, the variable measuring lending hours is positively associated with delinquency (column (6)). This finding may be due to suboptimal applications taking longer to process. If so, it implies that loan officers on average correctly assess the risk profile of different loans.

4.4. Evidence from Home Loans

Table 8 presents the results of the delinquency analysis for home loans. Our data on home loans allow us to explore the impact of several variables that are not available in the datasets for the other two loan categories. Column (1) presents our baseline regression results. Column (2) adds household size dummies. Column (3) includes coaching hours, which differ from lending hours in that they involve Native CDFI engagement to teach the borrower how to successfully repay their mortgage loan. Column (4) adds logged savings. Column (5) drops the household income variable and instead includes the debt-to-income ratio. Column (6) simultaneously includes all explanatory variables from the previous columns (except for household income, which is dropped, since we include the debt-to-income ratio).

Credit score is, once more, robustly and negatively associated with delinquency. From the demographic factors, being female is positively associated with delinquency. Our point estimates suggest that being female is associated with a 6.3-8.8 percentage point increase in the likelihood of delinquency relative to being male. However, this result is especially difficult to interpret as a pure gender effect because many home loan applications have co-applicants for whom we do not have data and who likely blur the gender effect. Neither coaching hours nor savings are significantly associated with the prospects of home-loan delinquency. Including the debt-to-income ratio (column (5)) shows a negative relationship between this variable and delinquency. The direction of the relationship is surprising, however the coefficient is only borderline statistically significant. In addition, when we include all explanatory variables at once (column (6)), the statistical significance disappears. This is interesting because the debt-to-income ratio is used by lenders to gauge the ability of borrowers to make their monthly payments. Our analysis shows that, in Native communities, the corresponding metric appears to be a rather weak signal of a borrower's repayment discipline when taking into account other factors.

4.5. Evidence from Other Consumer Loans

Table 9 presents the results of the delinquency analysis for other consumer loans. In the corresponding data, the borrower’s credit score is missing for an especially large number of loans. Thus, even though the reason why the credit score is missing for a particular loan is not known to us, incorporating loans with missing credit scores into the estimation seems especially important in this context. In investigating the determinants of delinquency for this loan category, we therefore adopt a different approach to modeling the effect of the credit score. Rather than postulating a linear relationship between loan delinquency prospects and the credit score, and thus restricting our analysis only to loans with a non-missing credit score, we create credit score bins based on credit score value and include a separate category for loans where the borrower's credit score is missing. We construct the credit score bins based on credit score ranges used by credit bureaus to rate potential lenders, as follows: an 800 to 850 credit score corresponds to an "excellent" rating, 740-799 to "very good", 670-739 to "good", 580-669 to "fair", and 300-579 to "poor". Aside from this change in modeling the effect of the credit score, the estimated regression mirrors the baseline specification in the previous result tables.

As in the regression results for business and home loans, we find that a higher credit score is negatively associated with delinquency of other consumer loans. However, unlike in the case of the other categories of loans, in the context of consumer loans, household income is statistically significantly negatively associated with delinquency. The data further show that the prospects of delinquency of other consumer loans are higher when the borrower self-identifies as AIANNH. However, there are only seven non-AIANNH borrowers in the sample used to generate the estimates shown in Table 9. All seven borrowers took out credit-builder loans that naturally tend to result in lower delinquency. We find the same effect of education on delinquency as in the case of other loan categories: all else equal, loans involving borrowers with less than a high school education have lower prospects of delinquency than the loans involving borrowers with high school education or higher. As mentioned previously, this finding is driven by the particular type of consumer loans, especially the credit-builder loan, normally extended to borrowers with less than a high school education.

5. Conclusion

As Native CDFIs gain prominence within the financial landscape of Indian Country, we continue to develop our understanding of the operations of the Native CDFI industry. This paper has provided the first systematic quantitative inquiry into the lending practices of Native CDFIs. Using loan-level data, we have focused on loan and client characteristics as well the determinants of loan delinquency for various categories of loans. Our descriptive analysis shows that Native CDFIs closely follow their mission and provide a variety of products to a range of borrowers in diverse circumstances. These circumstances include limited credit histories, which are partially stemming from historical barriers to access to credit in Indian country. Our data indicate that Native CDFIs indeed offer a significant number of credit-builder consumer loans and micro business loans.

Our central substantive finding is that a lending model that explicitly incorporates borrower-level information beyond the credit score, income, and other conventional loan-performance metrics could be an especially well-suited approach for Native CDFIs. Specifically, we demonstrate that although the borrower's credit score is on its own predictive of delinquency of Native CDFI loans, alternative borrower-level measures, such as those that reflect the borrower's character (in the context of business loans) and their level of engagement with the lender (for all loan categories), are empirically at least as important predictors of loan performance as conventional metrics. Because not all Native CDFIs collect the relevant information, this finding is admittedly obtained based on limited data. Nevertheless, it is suggestive of the prominence of nuanced, client-oriented lending practices in the Native CDFI industry.

Our research therefore also calls for improvements in data collection systems used in the Native CDFI industry. Our analysis suggests that all Native CDFIs would likely benefit from systematic collection of community-informed data on individual borrowers and business clients. The corresponding measures could then be included in the risk assessment models used by Native CDFIs as complements to conventional loan-performance metrics. In addition, consistent reporting of the measures of client coaching and advising, which are important components of Native CDFIs' approach, would be valuable for establishing the optimal level of coaching and advising. But data recording is costly, and thus external grant support for data management systems and for coaching/advising staff would be helpful. Finally, to understand the success of individual Native CDFIs, as well as the Native CDFI industry as a whole, it would be beneficial to develop industry-wide outcome and performance measures (McCall and Hoyman, 2021; Rausch, 2012). Of course, because the unique mission of the Native CDFI industry renders it distinct not only from conventional lenders but also from the CDFI industry at large, the corresponding performance metrics will likely have to reflect the distinct socioeconomic and cultural characteristics of Native communities.

The side-by-side report compiled by Oweesta Corporation in 2021 gives a sense of the collective impact of the industry from data aggregated from 28 Native CDFIs in 2020: 2,734 provided loans, totaling $71,276,743, issued to 2,930 AIANNH borrowers. Given the number of clients served, the amount of money lent to AIANNH borrowers, and the breadth of products that Native CDFIs offer to Native communities, Native CDFIs very significantly contribute to filling a major gap in access to credit and financial development in Indian Country. Future research should attempt to estimate the unmet demand for Native CDFI products. Such information could further quantify the importance of Native CDFIs for Native communities and stimulate the flow of additional capital into the Native CDFI industry.

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Table 1: List of Native CDFI participants

Organization	Year established	State	Reservation/tribal groups served
Lakota Funds	1986	SD	Pine Ridge Reservation
Sequoya Fund	1996	NC	Eastern Band of Cherokee Indians
Four Directions Development Corporation	2001	ME	Penobscot, Maliseet, Mi'kmaq, and Passamaquoddy
Cook Inlet Lending Center	2001	AK	Cook Inlet Region
Mazaska Owecaso Otipi Financial	2004	SD	Oglala Sioux Tribe, Pine Ridge Reservation, and enrolled members of other federally recognized tribes in South Dakota
Tiwa Lending Services	2012	NM	Isleta Pueblo
First American Capital Corporation	2002	WI	All tribal communities in Wisconsin
Four Bands Community Fund	2000	SD	Cheyenne River Sioux Reservation
Citizen Potawatomi Community Development Corporation	2003	OK	Citizen Potawatomi Nation

Chi Ishobak	2005	MI	The Pokagon Band of Potawatomi Indians
Chehalis Tribal Loan Fund	2007	WA	Chehalis Reservation

Table 2: Number of loans by loan type

Broad Loan Category	Loan Type	Number of Loans
Business Loans (total)		484
	Business Loan	149
	Commercial w/ Real Estate	56
	Equipment/Inventory	19
	Line of Credit	28
	Micro	188
	Vehicle	36
	Other Business	8
Home Loans (total)		305
	1st Mortgage	94
	2nd Mortgage	206
	Construction	5
Other Consumer Loans (total)		1,276
	Auto	486
	CPN Employee	469
	Consumer Loan	128
	Credit-builder	147
	Debt Consolidation	19
	Emergency	14
	Home Improvement	7

	Rental Assistance	6
Total		2,067

Table 3: Number of loans by delinquency and loan category

	Business	Home	Consumer	Total
Not delinquent	401	280	1,120	1,801
Delinquent	83	25	147	255
Missing	0	0	11	11
Total	484	305	1,278	2,067

Notes: A delinquent loan is a loan that has been delinquent at any point during the loan process and by any amount. A Not Delinquent loan has never been delinquent. The dataset also has some missing information on delinquency status.

Table 4: Credit scores by loan category and delinquency

		Mean	S.D.	Min	Max
Business	Total	649	69.1	468	810
	Not delinquent	661.9	65.8	491	810
	Delinquent	601.0	59.6	468	765
Home	Total	697	54.9	511	814
	Not delinquent	700.9	54.6	511	814
	Delinquent	657.5	41.8	564	814
Consumer	Total	587.2	68.5	445	757
	Not delinquent	588.8	68.2	445	757
	Delinquent	559.1	67.1	467	735

Notes: (n = 1220); Some CDFIs assigned a score of 300 to about 150 other consumer loan borrowers when a credit score was missing. For the purposes of this analysis, we treat those scores as missing.

Figure 1: Credit score frequency by loan category

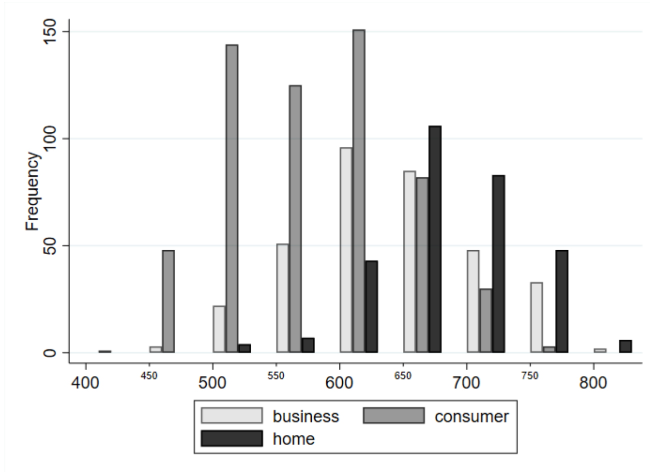

Figure 2: Distribution of loan amount by loan category

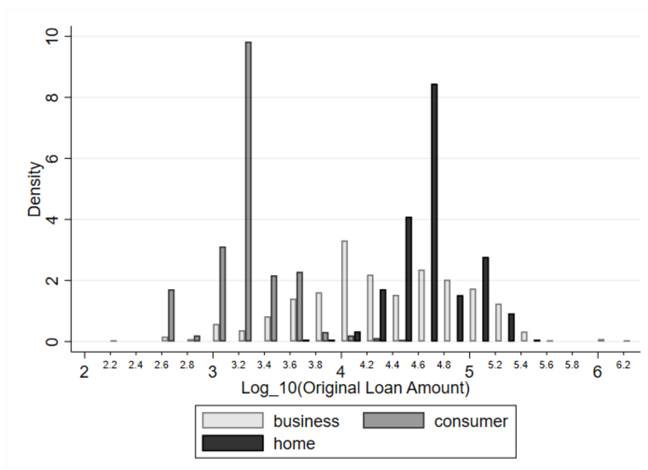

Figure 3: Histogram of closing dates for all loans

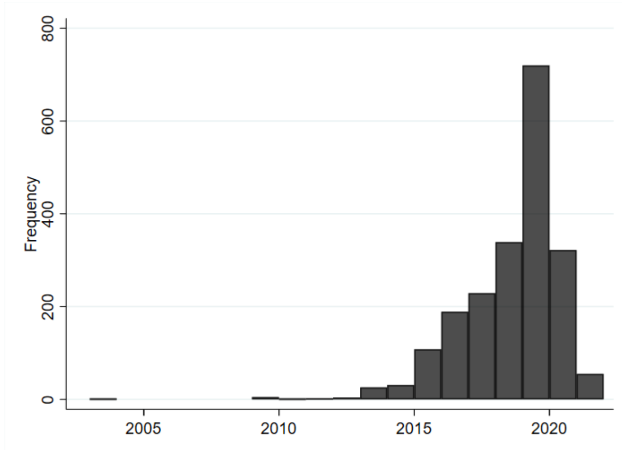

Table 5. The determinants of delinquency, combined loan data

Dependent variable: Delinquent =1 if loan ever delinquent		
Explanatory variables	(1)	(2)
Credit Score	-0.0007***	-0.0007***
	(0.0001)	(0.0001)
Log Household Income	-0.0060	-0.0046
	(0.0132)	(0.0132)
Female	0.0028	0.0034
	(0.0163)	(0.0164)
AIANNH	0.0352	0.0379
	(0.0318)	(0.0322)
Age of Borrower	-0.0002	-0.0002
	(0.0005)	(0.0005)
High School or Associate Degree	0.1655***	0.1651***
	(0.0507)	(0.0514)
Some College	0.0886*	0.0909*
	(0.0485)	(0.0500)
Bachelor's Degree or Higher	0.1064**	0.1119**
	(0.0517)	(0.0527)
Client Engagement: Somewhat Engaged		-0.1285***
		(0.0401)
Client Engagement: Well Engaged		-0.0423
		(0.0461)
Native CDFI-by-Loan Type FE	Yes	Yes

Observations	997	997
R-squared	0.134	0.138

Notes: The table reports OLS results. The dependent variable is Delinquent, a dummy equal to 1 if loan was ever delinquent. Native CDFI-by-Loan Type fixed effects are included but not reported. Omitted categories are: less than high school for education (an indicator for missing education is included in the regression but not reported in table); not engaged for client engagement; and non-AIANNH for ethnicity (an indicator for missing ethnicity is included in the regression but not reported in table). Heteroscedasticity-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6. The determinants of delinquency, business loan data

Dependent variable: Delinquent =1 if loan ever delinquent					
Explanatory variables	(1)	(2)	(3)	(4)	(5)
Credit Score	-	-	-	-	-
	0.0012***	0.0013***	0.0012***	0.0014***	0.0014***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Log Household Income	0.0450	0.0326	0.0447	0.0687	0.0561
	(0.0284)	(0.0394)	(0.0285)	(0.0446)	(0.0458)
Female	-0.0596	-0.0334	-0.0628	-0.0594	-0.0284
	(0.0454)	(0.0565)	(0.0451)	(0.0537)	(0.0617)
AIANNH	-0.0048	-0.0341	0.0005	-0.0221	-0.0306
	(0.0458)	(0.0523)	(0.0467)	(0.0642)	(0.0653)
Age of Borrower	0.0007	0.0034	0.0008	0.0010	0.0030
	(0.0014)	(0.0025)	(0.0015)	(0.0021)	(0.0028)
High School or Associate Degree	0.2751**	0.3604**	0.2898**	0.3248**	0.3474**
	(0.1107)	(0.1408)	(0.1336)	(0.1278)	(0.1601)
Some College	0.1317	0.1028	0.1446	0.0905	0.0772
	(0.1134)	(0.1319)	(0.1312)	(0.1337)	(0.1491)
Bachelor's Degree or Higher	0.2088*	0.1835	0.2273	0.1632	0.1372
	(0.1209)	(0.1362)	(0.1442)	(0.1357)	(0.1590)
Less Commitment to Business			-0.0737		-0.0338

			(0.1483)		(0.1616)
More Commitment to Business			-0.0393		-0.0052
			(0.1358)		(0.1483)
Business History Months		-0.0011**			-0.0011*
		(0.0005)			(0.0006)
Log Equity Invested				-0.0036	-0.0044
				(0.0050)	(0.0052)
Native CDFI FE	Yes	Yes	Yes	Yes	Yes
Observations	238	180	238	169	160
R-squared	0.265	0.266	0.267	0.263	0.258

Notes: The table reports OLS results. The dependent variable is Delinquent, a dummy equal to 1 if loan was ever delinquent. CDFI fixed effects are included but not reported. Omitted categories are: less than high school for education (an indicator for missing education is included in the regression but not reported in table); no commitment to business for commitment to business; and non-AIANNH for ethnicity (an indicator for missing ethnicity is included in the regression but not reported in table). Heteroscedasticity-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Determinants of Delinquency, business loans data (Four Bands Community Fund only)

Dependent variable: Delinquent =1 if loan ever delinquent						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.0018***	-0.0011	-0.0010	-0.0010	-0.0010	-0.0010
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Log household income	0.0452	0.0679	0.0424	0.0625	0.0819	0.0733
	(0.0600)	(0.0562)	(0.0592)	(0.0586)	(0.0571)	(0.0574)
Female	-0.0629	-0.0176	-0.0012	-0.0278	-0.0234	0.0457
	(0.0825)	(0.0838)	(0.0845)	(0.0847)	(0.0842)	(0.0823)
AIANNH	-0.0322	-0.1410	-0.1382	-0.1324	-0.0779	-0.1470
	(0.1460)	(0.1448)	(0.1405)	(0.1481)	(0.1468)	(0.1597)
Age of Borrower	0.0018	0.0020	0.0027	0.0021	0.0017	0.0017
	(0.0030)	(0.0029)	(0.0031)	(0.0030)	(0.0029)	(0.0031)
High School or Associate Degree	0.3488**	0.3263**	0.3234**	0.3448**	0.3277**	0.3160**
	(0.1477)	(0.1333)	(0.1400)	(0.1535)	(0.1354)	(0.1482)
Some	0.1374	0.0753	0.0342	0.0909	0.0732	0.0396

College						
	(0.1605)	(0.1506)	(0.1488)	(0.1674)	(0.1521)	(0.1617)
Bachelor's Degree or Higher	0.2215	0.1735	0.1184	0.2022	0.1489	0.0842
	(0.1526)	(0.1359)	(0.1359)	(0.1558)	(0.1358)	(0.1364)
Character Score		-0.1281***	-0.1257***	-0.1334***	-0.1211***	-0.1039**
		(0.0414)	(0.0406)	(0.0413)	(0.0417)	(0.0420)
Less Commitment to Business				-0.1016		
				(0.1490)		
More Commitment to Business				-0.0420		
				(0.1326)		
Business History Months			-0.0013			
			(0.0009)			
Log Equity Invested					0.0026	

					(0.0165)	
Lending Hours						0.0253**
						(0.0110)
Observations	100	100	99	100	99	92
R-squared	0.205	0.291	0.289	0.294	0.283	0.351

Notes: The table reports OLS results. The dependent variable is Delinquent, a dummy equal to 1 if loan was ever delinquent. Omitted categories are: less than high school for education (an indicator for missing education is included in the regression but not reported in table); no commitment to business for commitment to business; and non-AIANNH for ethnicity (an indicator for missing ethnicity is included in the regression but not reported in table). Heteroscedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Determinants of Delinquency, home loans data

Dependent variable: Delinquent =1 if loan ever delinquent						
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
Credit Score	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.066**	0.081**	0.065**	0.063**	0.064**	0.077**
	(0.030)	(0.033)	(0.031)	(0.031)	(0.030)	(0.034)
AIANNH	0.032	0.032	0.031	0.032	0.031	0.031
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Age of Borrower	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School or Associate Degree	0.046	0.045	0.046	0.042	0.046	0.041
	(0.039)	(0.041)	(0.039)	(0.040)	(0.040)	(0.042)
Some College	-0.017	-0.009	-0.017	-0.025	-0.018	-0.015
	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)
Log Household Income	0.017	0.009	0.012	0.025		
	(0.042)	(0.047)	(0.044)	(0.041)		
Household size 2		-0.011				-0.015
		(0.043)				(0.044)
Household size 3		-0.059				-0.050

		(0.042)				(0.041)
Household size 4		0.058				0.070
		(0.055)				(0.050)
Household size 5 or more		-0.003				0.005
		(0.065)				(0.062)
Coaching Hours			0.001			0.001
			(0.001)			(0.001)
Log Savings				-0.015		-0.014
				(0.012)		(0.011)
Debt-to-Income Ratio					-0.022*	-0.014
					(0.012)	(0.012)
Native CDFI FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	259	259	258	258	259	257
R-squared	0.140	0.155	0.141	0.153	0.140	0.170

Notes: The table reports OLS results. The dependent variable is Delinquent, a dummy equal to 1 if loan was ever delinquent. CDFI fixed effects are included but not reported. Omitted categories are: less than high school for education (an indicator for missing education is included in the regression but not reported in table); one-person household for household size; and non-AIANNH for ethnicity (an indicator for missing ethnicity is included in the regression but not reported in table). Heteroscedasticity-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Determinants of Delinquency, other consumer loans data

Dependent variable: Delinquent =1 if loan ever delinquent	
Explanatory variables	(1)
Credit Score 580-669 (fair)	-0.0255
	(0.0215)
Credit Score 670-739 (good)	-0.0394
	(0.0243)
Credit Score 740-799 (very good)	-0.0792***
	(0.0302)
Log Household Income	-0.0253*
	(0.0142)
Female	0.0009
	(0.0192)
AIANNH	0.1271**
	(0.0521)
Age of Borrower	-0.0004
	(0.0006)
High School or Associate Degree	0.1670***
	(0.0525)
Some College	0.1333**
	(0.0568)
Bachelor's Degree or Higher	0.0499
	(0.0459)
Native CDFI FE	Yes
Observations	652

R-squared	0.062

Notes: The table reports OLS results. The dependent variable is Delinquent, a dummy equal to 1 if loan was ever delinquent. CDFI fixed effects are included but not reported. Omitted categories are: less than high school for education (an indicator for missing education is included in the regression but not reported in table); credit score below 580 for credit score bins (an indicator for missing credit score is included in the regression but not reported in the table); and non-AIANNH for ethnicity (an indicator for missing ethnicity is included in the regression but not reported in table). Heteroscedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.