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Beyond conventional models: Lending by Native Community Development Financial Institutions

Valentina Dimitrova-Grajzl[1] | **Peter Grajzl**[2,3] | **Joseph Guse**[4] | **Michou Kokodoko**[5] | **Laurel Wheeler**[5,6]

[1]Department of Economics and Business, Virginia Military Institute, Lexington, Virginia, United States

[2]Department of Economics, Washington and Lee University, Lexington, Virginia, United States

[3]CESifo, Munich, Germany

[4]Community Development and Engagement, Federal Reserve Bank of Minneapolis, Minneapolis, Minnesota, United States

[5]Center for Indian Country Development, Federal Reserve Bank of Minneapolis, Minneapolis, Minnesota, United States

[6]Department of Economics, University of Alberta, Edmonton, Alberta, Canada

Correspondence
Laurel Wheeler, Center for Indian Country Development, Federal Reserve Bank of Minneapolis, 90 Hennepin Ave, Minneapolis, Minnesota, United States.
Email: laurel.wheeler@mpls.frb.org

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Abstract

Native Community Development Financial Institutions (Native CDFIs) have become an increasingly important source of credit and financial services in the areas on or near American Indian reservations in the United States. Guided by a conceptual framework developed on the basis of the related finance literature and drawing on loan-level data from eleven Native CDFI loan funds, we offer the first systematic quantitative analysis of lending in the Native CDFI industry. As hypothesized, 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, hard information-based, measures of client risk, and alternative, soft information-based, community-informed and character-based measures. Overall, these findings lend strong support to holistic approaches for assessing client creditworthiness for Native CDFI operations. 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 Native communities.

KEYWORDS
delinquency, Indian Country, lending, Native CDFIs, relationship lending

JEL CLASSIFICATION
G21, O16, J15, P43

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 (American Indian reservations, allotments, and communities), there exist several barriers to accessing credit, including 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), a percentage 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 twenty certified CDFIs are classified as Native CDFIs that predominantly target and serve American Indian, Alaska Native, and Native Hawaiian consumers (Community Development Financial Institutions Fund, 2021).[3]

[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).

[3] As of February 2023, there were 1396 Certified CDFIs operating in the United States (Community Development Financial Institutions Fund, 2023). CDFI Certification is a designation given by the US Department of Treasury's CDFI Fund. The CDFI Fund was established in 1994.

Despite the increasing importance of Native CDFIs as sources of credit in Native communities, little is known about the Native CDFI industry at large. What are some salient features of the Native CDFI industry when it comes to lending? To what extent and through what means do Native CDFIs facilitate financial inclusion? What factors shape the performance of Native CDFI loans? And what lending technologies, especially with regard to sources of information on borrowers, do Native CDFIs rely on in extending credit? These central questions have not been empirically investigated in the context of the Native CDFI industry.

In this paper, we provide the first systematic quantitative, loan-level inquiry into the operations of the Native CDFI industry. To this end, we first contextualize the Native CDFIs and their activity in the broader literature on microfinance, financial inclusion, and lending technologies. In so doing, we develop specific hypotheses about Native CDFI lending. We then subject our hypotheses to empirical scrutiny using several years of originally collected loan-level data from eleven Native CDFIs, the largest group of Native CDFIs that has ever been the subject of empirical investigation using loan-level data.

Our paper thereby advances the emerging literature on Native CDFIs and lending in Indian Country. Due to a dearth of data, existing contributions on Native CDFIs have been predominantly case studies of individual Native CDFIs or descriptive analyses that take a narrow focus on one facet of Native CDFI operations (e.g., Jorgensen and Taylor, 2015; Pickering and Mushinski, 2001; Dewees and Sarkozy-Banoczy, 2008). The scholarship that is more generalizable to the Native CDFI industry as a whole has focused on the Native CDFI history and typology, as opposed to lending (Kokodoko 2015, 2017), or indirectly linked Native CDFI activity to credit outcomes of individuals residing in or near Native communities (Dimitrova-Grajzl et al., 2022). Our analysis, in contrast, offers evidence-based insight into the lending operations of Native CDFIs and the performance of loans extended directly by Native CDFIs.

The paper proceeds as follows. Section 2 presents our theoretical framework and develops our hypotheses. Section 3 introduces our data and offers a descriptive account of the characteristics of Native CDFI loans and clients. Section 4 describes and discusses an empirical analysis of the predictors of delinquency in Native CDFI loans. Section 5 concludes.

2 | NATIVE CDFIS AND LENDING: THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

CDFIs provide financial products and development services that are "tailored to the needs of consumers and small businesses located in low- to moderate-income communities and other distressed markets that are not fully served by traditional financial institutions" (Kokodoko 2015). Native CDFIs predominantly target and serve Native communities—50% or more of their activities are focused on serving American Indians, Alaska Natives, and/or Native Hawaiians. Approximately 5% of certified CDFIs are classified as Native CDFIs (Community Development Financial Institutions Fund, 2021).

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).

Native CDFIs therefore share many of the traits of microfinance institutions (MFIs) striving to facilitate access to credit, combat financial exclusion, and address economic inequalities in lower income communities across the world (see, e.g., Morduch, 1999; Fouillet et al., 2013; Cai et al., 2023). Much like other MFIs, Native CDFIs emphasize a dual mandate of financial sustainability and social responsibility. With the aim of improving financial inclusion, Native CDFIs share the MFIs' objective to lend to underprivileged borrowers with scant or no prior credit histories; in other words, clients largely excluded from the formal banking sector.

Yet at the same time, Native CDFIs differ from typical MFIs in the developing world in the nuances of lending products and contracts. For example, group lending, a core financial innovation used by early MFIs (Sengupta and Aubuchon, 2008), was initially adopted but soon abandoned in Indian Country due to the lack of fit with the nature of family ties, rules of behavior, and general social organization in Native communities (see, e.g., Pickering and Mushinski, 2001). Moreover, the types of loan products and contractual approaches (e.g., use of collateral) employed by Native CDFIs are relatively more in line with those utilized by conventional lenders than those employed by some MFIs operating in low-income countries.

Native CDFIs differ from MFIs serving developing countries with respect to the specifics of the institutional and social environment in which they operate. In Indian Country, financial exclusion might arise for reasons other than the informational opacity of borrowers' credit histories and lack of financial literacy, which naturally lead to curtailed supply of and demand for credit in the areas targeted by the MFIs globally (Beck, 2015). In the US context there have also been enduring concerns about mainstream lenders' discrimination against Native communities (Community Development Financial Institutions Fund, 2001). Existing evidence shows, for example, that consumers residing in a predominantly American Indian neighborhood are awarded lower bankcard credit limits than consumers residing in neighborhoods where the share of American Indian residents is low, all else equal (Dimitrova-Grajzl et al., 2018). In Native communities as a whole, mainstream lenders may therefore be systematically choosing to leave good credit risks unfunded, a practice referred to as redlining (see, e.g., Tootell 1996; Campbell et al., 2008; Cohen-Cole, 2011).

For all these reasons, Native CDFIs are expected to play an especially vital role in facilitating credit and promoting financial inclusion in Native communities. We thus posit the following hypothesis:

H1: Native CDFIs offer a variety of loan products and serve diverse borrowers.

Native CDFIs deal with especially informationally opaque borrowers—clients with no or very limited credit histories. Adverse selection and moral hazard problems, therefore, are non-trivial. However, given Native CDFIs' positioning in or near the Native communities, loan officers interact with clients repeatedly and have access to community-based information about clients. In gathering proprietary insights about clients, Native CDFIs thereby produce soft information, for example about the borrower's behavior, character, and reliability, much like other small lenders serving informationally opaque borrowers (see, e.g., Berger and Udell, 2002; Berger et al., 2005; Berger and Black, 2011; Uchida, 2011). Accordingly, we expect Native CDFIs to rely heavily on a lending technology that employs soft information and is relationship-based, as opposed to one that relies exclusively on hard information (e.g., credit scores and balance sheets) and is therefore transactions-based (Berger and Udell, 2006).

Indeed, Native CDFIs are uniquely positioned to productively use soft information on two grounds. The first is that Native CDFIs possess a thorough understanding of local social norms and culture, a key aspect of the social environment that facilitates reliance on relationship-based lending (Berger and Udell, 2006). The second is that Native CDFIs are comparatively small in size and rely on a flat organizational structure that entails the delegation of substantive authority to loan officers. The latter are critical in interpreting and using soft information (see, e.g., Tchakoute Tchuigoua, 2022; Godfroid, 2019) that is challenging to communicate, verify, and rely on, especially for lenders employing more hierarchical organizational structures (Berger and Udell, 2002; Stein, 2002; Degryse, Laeven et al., 2009). We therefore hypothesize:

H2: Native CDFIs employ relationship-based lending technology, thereby combining the use of hard and soft information.

Theory and evidence outside of Indian Country suggest that a lending technology based on a combination of hard and soft information can improve lender and borrower outcomes (e.g., Petersen and Rajan, 1994; Scott, 2006; Behr et al., 2011). In particular, the combining of hard and soft information alleviates lenders' informational problems, leading to fewer defaults (Agarwal and Hauswald, 2010; Grunert et al. 2005; Chen et al. 2015; Cornee, 2019), an outcome that in turn facilitates access to credit and financial inclusion. Consistent with this perspective, data suggest that relationship-based lending has been instrumental in relaxing borrowers' credit constraints especially during economic downturns (Beck et al., 2018; Ferri et al., 2019; Bolton et al., 2016; Tchakoute Tchuigouaa et al., 2020).

At the same time, relationship lending and use of soft information also have their drawbacks. In the absence of competition between lenders, for example, extensive reliance on relationship lending can lead to hold-up problems due to the lender's exploitation of its market power vis-à-vis the borrower and soft-budget problems due to the lender's reluctance to rigorously enforce the terms of the lending contract (see, e.g., Boot, 2000; Degryse, Ongena et al., 2009; Kysucky and Norden, 2016). Such concerns may certainly arise in specific circumstances. We, however, have no empirical or anecdotal evidence that these two issues are a concern for Native CDFIs. The focus of Native CDFIs on ensuring that lending does no harm to the borrower also mitigates both issues. Overall, we would anticipate the benefits to the lenders and borrowers in Indian Country of the combined use of hard and soft information to outweigh the costs. We therefore hypothesize:

H3: The Native CDFIs' use of soft information aids loan performance.

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 describe our data. We then provide insights based on the combined sample of loans that aggregates business, home, and other consumer loans. Finally, we examine each individual loan category. Taken together, the descriptive analysis in this section addresses our hypothesis H1, that Native CDFIs offer a variety of loan products and serve diverse borrowers.

3.1 | Data description

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

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

project on lending and risk analysis in the Native CDFI industry.[4] Sweet Grass Consulting invited 14 Native CDFIs; 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

[4] 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/).

TABLE 2 Number of loans by loan type.

Broad Loan Category	Loan Type	Number of Loans
Business Loans (total)		484
	Business Loan	149
	Commercial with 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

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 3.2 and 4 we elaborate on and discuss the implications of this sampling decision for our analysis.

3.2 | Combined sample

The dataset contains cross-sectional, loan-level data for 484 business loans, 305 home loans, and 1276 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, microloans (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

TABLE 3 Number of loans by delinquency and loan category.

	Business	Home	Consumer	Total
Not delinquent	401	280	1120	1801
Delinquent	83	25	147	255
Missing	0	0	11	11
Total	484	305	1278	2067

Note: 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.

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.[5] 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.[6] The oversampling of delinquent loans in addition to the use of the broad definition of delinquency further explain 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. The Native CDFIs in our sample collect data on credit scores that have been calculated and reported by credit bureaus such as Equifax. Credit score calculations rely on information about the number and types of accounts the prospective borrower has, whether bills are paid on time, how much available credit the prospective borrower is using, whether there are any collections against the prospective borrower, the amount of outstanding debt, and the age of the prospective borrower's financial accounts. When observed, credit scores vary between 300 and 850, with scores above 740

[5] Our data only provide information about whether the Native CDFI has declared a loan delinquent and do not provide information about other types of delays in repayment. The definition of delinquency is specific to each Native CDFI and the definition is not standardized. Anecdotally, many Native CDFIs declare a loan delinquent based on a 90-day delay in repayment; some declare a loan delinquent based on a 60-day delay in repayment; and a further group of Native CDFI might use yet another delinquency threshold. Our broad definition of delinquency is adopted to facilitate comparison across Native CDFIs.

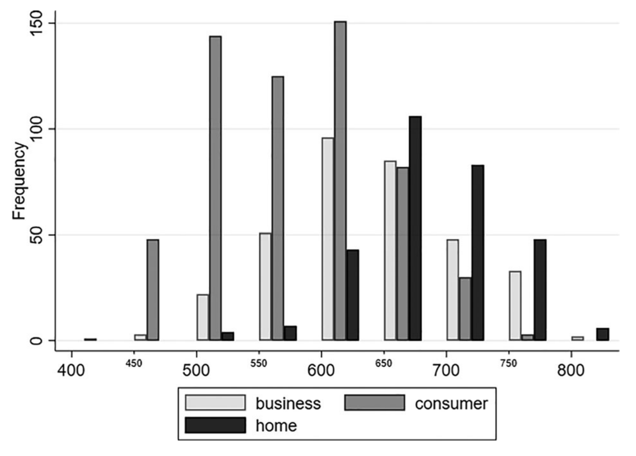
[6] Oweesta and Sweet Grass Consulting asked participating Native CDFIs to go back into their databases as far as they needed to go to meet a threshold number of delinquent loans. In most cases, that number was approximately 30 delinquent loans. Not all Native CDFIs were able to reach the delinquency threshold because data extractions are costly and, oftentimes, require extensive data cleaning at a significant cost. Participating Native CDFIs had flexibility with respect to which loans they chose to extract from their database and share with the research team, although they had no incentive to select loans in a way that would influence our analysis.

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

Note: ($n = 1220$); 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.



considered very good/excellent. Individuals with scores below 670 are subprime borrowers and are likely to experience difficulty qualifying for loans at mainstream banks.[7]

Credit scores are often missing in our data. Out of 2067 loans in our dataset, only 1220 (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.[8] 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.

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

[8] In our preferred specifications, we implicitly assume that missing credit scores are due to data not being recorded. In Section 4.6, we discuss some of the implications of relaxing this assumption.

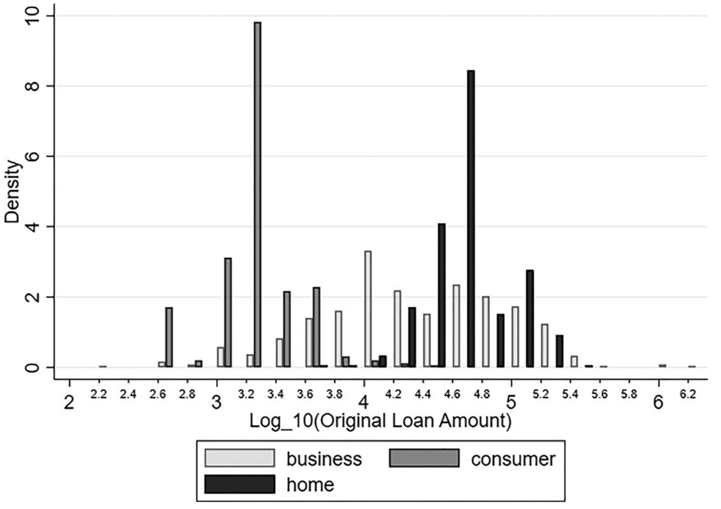


FIGURE 2 Distribution of loan amount by loan category.

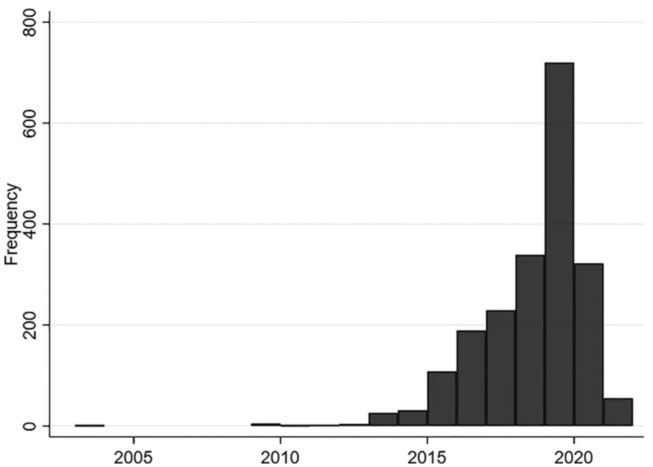


FIGURE 3 Histogram of closing dates for all loans.

Most business loans that appear in our dataset would be considered microloans.[9] Overall, we have 1487 loans (business, consumer, and home) with non-missing loan amount values. The mean loan amount is $33,672 and the median is $5500. 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.

[9] The CDFI Fund Transaction Level Reports' (TLR) definition of a microloan 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."

3.3 | 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, microloan, 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, 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.

3.4 | 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 to 2021. These include 94 first-mortgage loans, 5 construction loans, and 206 second-mortgage loans. The loan amounts for home loans range from $5547 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

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

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 and 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.

3.5 | Other consumer loans

We have information on 1278 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 $2544 and a median of $2085.

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, 59% of the loans from these two Native CDFIs 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.

3.6 | The main takeaways

The descriptive analysis in Sections 3.2–3.5 provide strong support in favor of our hypothesis H1. We show 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?

In terms of delays in repayment, flexibility in loan servicing is one of the key features of Native CDFIs that sets them apart from mainstream financial institutions.[11] But loan delinquency of course 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 subsamples by specific loan category. In so doing, we address both our hypothesis H2 (that Native CDFIs employ relationship-based lending technology) and our hypothesis H3 (that the use of soft information aids the performance of Native CDFI loans).

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.[12]

Our dependent variable is an indicator variable 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, an indicator for a female borrower, an indicator for an AIANNH borrower, borrower age (in years) at the closing date of the loan, and a set of indicator variables capturing the borrower's attained education level (below high school, high school or associate's 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.[13] In augmenting the baseline specification, we therefore add additional explanatory variables one at a time.[14]

In models exploiting the combined sample of business, home, and other consumer loans we always include fixed effects for Native CDFI by broad loan 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. Congruent with this perspective, we find significant differences in the share of missing data across Native CDFIs and by loan type (see Table A5 in the Appendix). In models drawing

[11] Native CDFIs can more easily adjust their lending terms to accommodate the needs of their borrowers when facing financial challenges (Community Development Financial Institutions Fund, 2019). This may include deferment, forbearance, and loan modifications, as well as expansion loans to help small businesses further enlarge their operations. There are many different approaches to dealing with cases of default, and there is considerable heterogeneity in the corresponding procedures both across Native CDFIs and by loan type.

[12] Our research design does not warrant clustering of standard errors either on the grounds of the sampling process or the basis of the assignment mechanism (see, e.g., Abadie et al., 2023). Moreover, our inclusion of either Native CDFI by loan category or Native CDFI fixed effects, emphasized in this section, should adequately absorb the corresponding common shocks (see, e.g., Cameron and Miller, 2015).

[13] In Section 4.5, we explore an alternative analysis that imputes missing values of demographic variables.

[14] Summary statistics for the different samples we draw on in the various empirical specifications are available upon request.

on data for a specific loan category, we instead control for Native CDFI fixed effects.[15] 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 3.2, 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.[16] 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 and engage in transactions-based lending, emphasize credit score and borrower income. We explore the predictive power of credit score and income. We find that credit score in 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.[17] Because a borrower's past delinquency and late payments may affect the borrower's current credit score as well as exert an independent effect on the current delinquency prospects beyond the effect of the credit score, we cannot rule out the possibility of endogeneity in our setting. For this reason, we again caution against interpreting the estimates as causal.

Unlike credit score, household income 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

[15] 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 in 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.

[16] 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 $2500 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.

[17] 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.

TABLE 5 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)
Client Engagement: Somewhat Engaged		-0.1285***
		(0.0401)
Client Engagement: Well Engaged		-0.0423
		(0.0461)
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 Associates 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)
Native CDFI-by-Loan Type FE	Yes	Yes
Observations	997	997
R-squared	0.134	0.138

Note: The table reports OLS results. The dependent variable is Delinquent, an indicator 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.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

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.

Consistent with our hypothesis H2, to predict 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 soft information-based measures of credit risk is a defining feature of relationship-based, and specifically 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.[18] The CBL model appears to be gaining traction in practice, but remains under-studied quantitatively. We explore the relationship between delinquency and several of the non-standard, soft information-based 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 indicator 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 indicator variables: 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 indicator variables 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, soft information-based, 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, ethnicity, and age—are not statistically significant predictors of loan delinquency. Surprisingly, the estimated coefficients on the indicators 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.[19] 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) as follows. Column (2) adds indicator variables for assessed levels of commitment to

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[18] 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."

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

TABLE 6 Determinants of delinquency, business loan data.

Dependent variable: Delinquent = 1 if loan ever delinquent			
Explanatory variables	**(1)**	**(2)**	**(3)**
Credit Score	-0.0012***	-0.0012***	-0.0014***
	(0.0003)	(0.0003)	(0.0004)
Log Household Income	0.0450	0.0447	0.0561
	(0.0284)	(0.0285)	(0.0458)
Less Commitment to Business		-0.0737	-0.0338
		(0.1483)	(0.1616)
More Commitment to Business		-0.0393	-0.0052
		(0.1358)	(0.1483)
Female	-0.0596	-0.0628	-0.0284
	(0.0454)	(0.0451)	(0.0617)
AIANNH	-0.0048	0.0005	-0.0306
	(0.0458)	(0.0467)	(0.0653)
Age of Borrower	0.0007	0.0008	0.0030
	(0.0014)	(0.0015)	(0.0028)
High School or Associates Degree	0.2751**	0.2898**	0.3474**
	(0.1107)	(0.1336)	(0.1601)
Some College	0.1317	0.1446	0.0772
	(0.1134)	(0.1312)	(0.1491)
Bachelor's Degree or Higher	0.2088*	0.2273	0.1372
	(0.1209)	(0.1442)	(0.1590)
Business History Months			-0.0011*
			(0.0006)
Log Equity Invested			-0.0044
			(0.0052)
Native CDFI FE	Yes	Yes	Yes
Observations	238	238	160
R-squared	0.265	0.267	0.258

Note: The table reports OLS results. The dependent variable is Delinquent, an indicator 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.
$^{***}p < 0.01$,
$^{**}p < 0.05$,
$^{*}p < 0.1$.

business, a variable we discuss below. Column (3) adds the covariate measuring the number of months that the business has existed as well as a measure of the value of invested equity.

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 1–3) and equity invested (column 3) are not systematically related to prospects of loan delinquency. However, credit score (columns 1–3) and longevity of the business (column 3) 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.[20]

The business loans data facilitate the cleanest test of our hypothesis H3 that Native CDFI use of soft information aids loan performance. We study the relationship between two different types of soft information and loan performance. First, a score of commitment to business is used by several Native CDFIs in our dataset. We include a set of indicator variables respectively indicating “more commitment to business” and “less commitment to business,” with “no commitment to business” as the omitted (benchmark) category (Table 6, columns 2 and 3). We do not find a statistically significant relationship between these variables and delinquency, although the point estimates are consistently negative, as anticipated.

Second, 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 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 their clients and build relationships with them. Based on these conversations, loan officers will 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 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 hard information-based credit risk measures such as the credit score and household income but without soft information-based credit risk measures (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 nonsignificant 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. This finding is consistent with our hypotheses H2 and H3, that the Native CDFIs combine the use of hard and soft information and that the use of soft information aids Native CDFI loan performance.

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

[20] According to the sample used to estimate the specification in column (3), 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.

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)**
Credit Score	-0.0018***	-0.0011	-0.0010	-0.0008
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Log Household Income	0.0452	0.0679	0.0625	0.0678
	(0.0600)	(0.0562)	(0.0586)	(0.0629)
Character Score		-0.1281***	-0.1334***	0.0910**
		(0.0414)	(0.0413)	(0.0434)
Less Commitment to Business			-0.1016	-0.0475
			(0.1490)	(0.1355)
More Commitment to Business			-0.0420	-0.0234
			(0.1326)	(0.1323)
Female	-0.0629	-0.0176	-0.0278	0.0593
	(0.0825)	(0.0838)	(0.0847)	(0.0858)
AIANNH	-0.0322	-0.1410	-0.1324	-0.0674
	(0.1460)	(0.1448)	(0.1481)	(0.1640)
Age of Borrower	0.0018	0.0020	0.0021	0.0027
	(0.0030)	(0.0029)	(0.0030)	(0.0036)
High School or Associates Degree	0.3488**	0.3263**	0.3448**	0.3395*
	(0.1477)	(0.1333)	(0.1535)	(0.1728)
Some College	0.1374	0.0753	0.0909	0.0293
	(0.1605)	(0.1506)	(0.1674)	(0.1751)
Bachelor's Degree or Higher	0.2215	0.1735	0.2022	0.0433
	(0.1526)	(0.1359)	(0.1558)	(0.1514)
Business History Months				-0.0009
				(0.0010)
Log Equity Invested				0.0058
				(0.0183)
Lending Hours				0.0258**
				(0.0111)
Observations	100	100	100	90
R-squared	0.205	0.291	0.294	0.350

Note: The table reports OLS results. The dependent variable is Delinquent, an indicator 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.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

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 on relationship- and character-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)–(4) of Table 7, we include as controls indicator variables indicating the level of commitment to business (column 3), as well as business history months, logged equity invested, and lending hours (column 4). Lending hours are defined as the total number of hours that a loan officer spent putting together the pertinent loan package and working towards closing. Interestingly, the variable measuring lending hours is positively associated with delinquency (column 4). 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 indicator variables. Column (3) includes coaching hours, logged savings, and the debt-to-income ratio. Coaching hours differ from lending hours in that they involve Native CDFI engagement to teach the borrower how to successfully repay their mortgage loan.

Credit score is, once more, robustly and negatively associated with delinquency. Thus, resonating with our hypothesis H2, the use of hard information in assessing credit risk is an integral part of Native CDFIs' relationship-based lending technology.

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, savings, nor the debt-to-income ratio are significantly associated with the prospects of home-loan delinquency. This result 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

TABLE 8 Determinants of delinquency, home loans data.

Dependent variable: Delinquent = 1 if loan ever delinquent			
Explanatory variables	**(1)**	**(2)**	**(3)**
Credit Score	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Log Household Income	0.017	0.009	0.008
	(0.042)	(0.047)	(0.050)
Female	0.066**	0.081**	0.078**
	(0.030)	(0.033)	(0.034)
AIANNH	0.032	0.032	0.031
	(0.053)	(0.053)	(0.053)
Age of Borrower	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
High School or Associates Degree	0.046	0.045	0.041
	(0.039)	(0.041)	(0.042)
Some College	-0.017	-0.009	-0.015
	(0.033)	(0.033)	(0.035)
Household size 2		-0.011	-0.016
		(0.043)	(0.043)
Household size 3		-0.059	-0.052
		(0.042)	(0.043)
Household size 4		0.058	0.068
		(0.055)	(0.055)
Household size 5 or more		-0.003	0.001
		(0.065)	(0.067)
Coaching Hours			0.001
			(0.001)
Log Savings			-0.014
			(0.012)
Debt-to-Income Ratio			-0.012
			(0.017)
Native CDFI FE	Yes	Yes	Yes
Observations	259	259	257
R-squared	0.140	0.155	0.170

Note: The table reports OLS results. The dependent variable is Delinquent, an indicator 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 Associates 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

Note: The table reports OLS results. The dependent variable is Delinquent, an indicator 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.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

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 800–850 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, confirming the importance of hard information-based measures as predictors of credit risk in Native CDFI lending, 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. 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.

4.6 | Robustness checks

In this subsection, we describe two robustness checks on our analysis, in particular examining the implications of the way we have handled missing data. We first discuss our primary approach to dealing with missing credit scores and summarize the results based on an alternative approach. Then, we discuss our main approach and alternative analysis aimed at addressing missing data on demographic variables.

Credit scores are missing for approximately 41% of the loans in our combined sample, with the majority of missing scores coming from consumer loans. Our preferred specifications treat missing credit scores as the result of non-systematic reporting gaps (with the exception of the other consumer loans analysis reported in Table 9). This approach treats all missing credit scores as missing at random and removes observations with missing credit scores from analysis. If credit scores are not truly missing at random, and if loans associated with missing scores are systematically different, our preferred approach may introduce bias. To test the implications of the assumption that credit scores are missing at random, we adopt an alternative approach that does not impose any assumptions about the nature of missing credit scores. 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. Estimates from this new analysis are reported in Tables A1–A4 in the Appendix. Our main results are qualitatively similar to the results reported in Tables 5–8.[21]

In our preferred specifications, we do not replace missing values of demographic variables. For two categorical variables, education and ethnicity, we created a "missing" category, which we included as a binary variable in our regressions. Ethnicity was coded as missing for 32% of the combined sample, and education was coded as missing for 73% of the combined sample. For other demographic variables, such as gender (missing for 30% of the combined sample) and age of borrower (missing for 33% of the combined sample), we did not attempt to account for missing values. Observations with missing values would have been excluded from the analysis. We conduct an alternative analysis that instead imputes missing demographic information as the median value of the given sample (i.e., the combined sample, the home loans sample, etc.). We perform this imputation for education, ethnicity, gender, and age, and we report the results of the new analysis in Tables A6–A10 in the Appendix. The imputation method does increase the number of observations in most of our regressions; however, because of the large number of missing values we have replaced, the explanatory power of our models and the precision of our estimates decreases

[21] We do not reproduce Table 9 in the Appendix because the analysis in Table 9 already includes binary variables for low credit scores and missing credit scores.

relative to our preferred specifications (reported in Tables 5–9). Our key findings, including our findings related to the role of hard information and soft information, remain unchanged.

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 and drawing on the literature on relationship lending, we have focused on investigating specific hypotheses pertaining to Native CDFI loan and client characteristics as well as the determinants of loan delinquency for various categories of loans.

Our analysis shows that, as hypothesized, 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 findings support the conjectures that Native CDFIs utilize a relationship-based lending technology and that the use of soft information aids Native CDFI loan performance. In particular, our evidence indicates that a lending model that explicitly incorporates borrower-level information beyond the hard information-based 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, soft information-based, 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 hard information-based metrics. Because not all Native CDFIs formally collect the relevant soft information-based metrics, 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: 2734 provided loans, totaling $71,276,743, issued to 2930 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 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.

ORCID

Laurel Wheeler https://orcid.org/0000-0002-7557-1153

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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